Concept, Design and Evaluation of Cognitive Task-based UAV Guidance

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***Abstract*—This paper discusses various aspects of automation for the integration of multiple, detached, unmanned sensor platforms into a military helicopter scenario. The considered scenario incorporates operating over unknown, potentially unsafe terrain including ad-hoc mission orders issued to the crew even during flight. Unmanned sensor platforms provide mission-relevant real-time reconnaissance and surveillance information to the crew and therefore lead to an increase in mission performance. To achieve this, the UAVs (Uninhabited Aerial Vehicles) shall be automated beyond the level of commonly used systems, i.e., autopilots and waypoint guidance. Instead the human operator shall be enabled to transfer authority to the unmanned platforms in a well-defined manner just like in tasking human subordinates. Automatic task execution is achieved by installing knowledge-based and goal-driven agents based on artificial cognition on the unmanned platforms for planning and decision-making. These agents allow the human operator to assign tasks to the UAVs on an abstraction level which is comparable to the supervision of human subordinates within a mission. This paper presents the concept and design of such artificial cognitive agents. A novel views on levels of automation will be discussed. The required knowledge driving the cognitive automation will be explained and the results of the evaluation of the system with subject matter experts will be discussed. The results, which include measures of the overall mission performance, operators' interaction, behaviour, workload, situation awareness and acceptance ratings, indicate that task-based UAV guidance is feasible, accepted and beneficial in military helicopter operations.**

Keywords - task-based guidance; goal-driven behaviour; artificial cognititive units; artificial cognition; level of automation

I. INTRODUCTION

The utilization of UAVs (Uninhabited Aerial Vehicles) as detached sensor platforms of a manned helicopter in a military scenario promises to enhance mission safety and effectiveness by allowing the crew to deploy sensors in dynamic and uncertain environments without exposing personnel to potential threats more than needed. Using unmanned vehicles for this purpose requires a change in the UAV guidance paradigm that enables a single human operator to control one or even multiple UAVs while being the commander of a manned aircraft. If those detached platforms were controlled by humans, a commander would just assign tasks referring to the mission context and the current situation and leave the details of task execution as well as the application of domain knowledge generating local tactical behaviours to the human subordinate. A way to incorporate this leadership concept in the guidance of uninhabited vehicles using such knowledge in a machine agent and the evaluation of a corresponding experimental system are first time described in [1]. A final evaluation experiment as described in [1] took place in May 2011. This paper extends the findings provided by [1] and describes the overall concept of task-based guidance, the system architecture, the knowledge base and the evaluation in more detail.

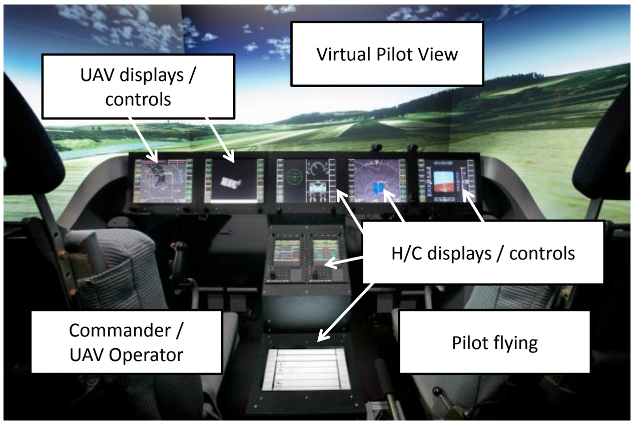

Figure 1. Helicopter simulator of the Institute of Flight Systems

Some current research approaches concerning UAV guidance allow the definition of scripts or plays [2] to define action sequences for one or multiple UAVs. Moreover, some of these systems also react to changes in the situation like a new threat along a flight route [3]. However, the resulting behaviours of these systems are solely defined at design-time. The underlying goals of the UAVs are not explicitly expressed in the system but are implicitly encoded in the implementation of the behaviours. With implicit goals, the system "simply makes guesses – statistically plausible guesses based on the designer's observations and hunches." [4]. This paper describes the system architecture that avoids most of the "guessing" by the application of knowledge and goals driving task-based, cooperative and cognitive UAV automation. Furthermore, various metrics that can be applied to automation of UAVs are presented. The resulting type of supervisory control shall avoid at least some of the issues of conventional automation by taking a step towards human-centred automation [5]. The resulting laboratory prototype has been integrated in the helicopter research flight simulator of the Institute of Flight Systems at the Universität der Bundeswehr München, which is shown in Figure 1, and evaluated in experiments with experienced German Army aviators. In these experiments, the pilots had to perform several, dynamic troop transport missions including an unscheduled combat recovery task with the support of the manned helicopter and three tactical UAVs.

The following sections present related work in the field of UAV guidance and the concepts behind the task-based guidance approach in general as well as its application to UAVs. Section IV illustrates different measures of automation in the domain of unmanned vehicles. Section V presents the system architecture of a simulation prototype including a short introduction into the concept of artificial cognitive units (ACUs) and a description of the knowledge base of a UAV. Finally, Section VI contains the description, measures and results of an experimental evaluation of the concept of task-based guidance.

II. Related Work

Most current research projects in the area of UAV guidance and mission management focus on solving problems in the field of trajectory generation [6] and management and the achievement of what is mostly referred to as “full autonomy” by the application of control algorithms [7].

This research concentrates on optimizing mission effectiveness, e.g., time or fuel consumption, within a given constraint set. However, such constraint sets and parameters are either static or the definition is left to the human operator or the experimenter. If the handling and monitoring of the control algorithms of multiple UAV is allocated to the commander of a manned helicopter, then the result is error-prone behaviour and high workload for the operator [8, 9]. Therefore, we present a system that integrates flight management, payload control and data links into one entity of automation. This entity uses its knowledge about the situation, the mission, the vehicle and its capabilities to provide an interface to the human operator that allows UAV guidance on a situation adaptive task level rather than sub-system handling. Instead of optimising isolated algorithms or use-cases, this approach aims for the integration of multiple unmanned vehicles into a highly dynamic military mission while allowing the commander of a manned helicopter to use the UAV capabilities at an abstraction level similar to commanding human subordinates, i.e., additional manned helicopters.

Previous publications focus on the requirements engineering [9] and global system design and test environment including the integration of assistant systems [10–12]. Moreover, [13] provides a detailed description of the software framework used in this work. This framework is currently undergoing a major redesign to reflect the feedback from various applications [14]. The main contribution of this paper consists of a discussion of the foundations of task-based guidance, its implementation for UAV guidance, the resulting levels of automation on various scales, a detailed description of the knowledge base as well as the experimental evaluation of the system.

III. Task-based Guidance

The concept of task-based guidance by sharing authority and common goals was first described by the military strategist Sun Tzu [15] around 500 BC. He noted the importance of sharing and pursuing common goals among all ranks to be successful. Consequently, the guidance of subordinates should not just consist of instructions but also include the reason and the objectives.

A. *Concept of tasks*

In this paper we define task as the combination of (1) a goal to achieve and (2) a transfer of authority to a subordinate in order to achieve that goal. Therefore, issuing tasks to a subordinate (who may be human or artificial agents) has several implications and requirements to the subordinate as well as to the supervisor.

Miller [16] lists six requirements for delegation relationships:

1. “The supervisor retains overall responsibility for the outcome of the work…” as well as the overall authority.
2. “if the supervisor wishes to provide detailed instructions, s/he can; when s/he wishes to provide only loose guidelines … s/he can do as well…”
3. “… the subordinate must have substantial knowledge about and capabilities within the domain.”
4. A supervisor has to know the limitations of the subordinate.
5. A common representation of tasks and goals has to be shared between supervisor and subordinate to communicate about tasks, goals and constraints.
6. “The act of delegation will itself define a window of control authority within which the subordinate may act.”

Based on those requirements the following consequences for designing an artificial subordinate can be derived:

- Following the first requirement, a subordinate must not be “fully autonomous”, i.e., a subordinate must not alter the goal to achieve. According to [16], a truly autonomous system would neither be ethical nor be useful, because it takes away responsibility and control from the human supervisor. Therefore, an artificial subordinate must not violate its “window of control authority” (requirement 6).
- Requirement 3 demands that an artificial subordinate shall be designed and implemented as knowledge based system. In combination with requirement 5, this leads to a *symbolic knowledge representation* which allows to use explicit knowledge for processing and communication.
- Requirement 5 as well as our definition of the term “task” leads to a *goal-driven system*, i.e., the overall behaviour of the system shall be defined by the goals pursued.
- To address requirement 2, the supervisor may choose to provide only tasks considered relevant to him or her. Consequently, it is the responsibility of the system, to *maintain a consistent task agenda*. This is accomplished by inserting missing tasks as required the mission to be accomplished, general domain knowledge and causality, e.g., knowing that a start procedure is required to be airborne.

It is obvious that a technical system capable of fulfilling those requirements and the above-mentioned conclusions is a very complex technical system by design. Billings [18] listed several negative characteristics of systems where humans have to supervise complex automation in general. Complexity in this context means that the system cannot fully be understood by the human operator in every state of the system or in every workload situation that may arise. The characteristics described by Billings are:

- *Brittleness* – The design of the automation limits its use cases to those defined by the designer. Outside of these limits, the behaviour of the automation is not defined. Further information about the relation between designer and operator of complex systems can be found in [19].
- *Opacity* – The operator of complex automation may have a wrong or incomplete model of the automation. The automation does not provide sufficient information to support a correct and complete model in every situation.
- *Literalism* – The automation does not have any knowledge about goals and intents of the operator, but executes its functions defined at design time. It does not and cannot check if those functions support the achievement of the operator's goals.

While automation complexity is inherent to the introduction of a new automation layer, the approach of task-based guidance attempts to reduce those negative effects. This is achieved by the following techniques in the design of task-based guidance systems:

- To address *brittleness*, domain specific practices and regulations, e.g., air space regulations in the aviation domain, shall be known to the automation and shall be pursued as goals rather than executed as hard wired functions. Due to the inherent knowledge-processing characteristics of cognitive automation, the system will strive to follow the regulations even in situations not foreseen by its designer.
- *Opacity* can be reduced by providing feedback on the abstraction level of task description. Using this abstraction level during task assignment, task processing, task execution and in the feedback about current and future tasks allows the human operator to build a mental model about the current and future state of the automation.
- In contrast to conventional, procedure-based automation, task-based guidance follows explicit and abstract objectives. This counteracts *literalism*, because the automation chooses functions (action alternatives) that pursue the task objectives with respect to the currently observed situation.

The following section describes the application of this concept to the guidance of UAVs.

B. *Application to UAV guidance*

Task-based UAV guidance aims at integrating multiple unmanned vehicles into a manned helicopter mission in a similar manner as integrating additional manned helicopters into the scenario. Therefore, the guidance of unmanned vehicles should be on an abstraction level that allows the allocation of a series of tasks to each UAV. These tasks are issued by the human operator and request the achievement of goals, e.g., the request of reconnaissance information about a landing site. The interpretation of the tasks and the use of on-board systems to fulfil these tasks are left to the UAV. The series of tasks is on a similar abstraction level as tasks assigned to a pilot during mission briefing in a conventional, manned helicopter mission.

Moreover, just like a human pilot, UAVs should also use opportunities of supporting the mission, e.g., by getting sensor information of nearby objects, without a direct command from the operator.

This implies UAV guidance and mission management on a level where one or more UAVs are controlled by tasks that use mission terms instead of waypoints and the request of results rather than in-detail configuration of flight control functions and sensor payload. The latter should be generated aboard the UAV by its on-board automation.

The tasks currently implemented in the experimental setup are:

- a ***departure*** task that respects basic air traffic regulations of the airfield and makes the UAV take off and depart via a given, named departure location.
- a ***transit*** task that causes a flight to a specific, named location. While being in transit, the UAV configures the on-board camera into forward looking mode. Known threats will be automatically avoided, if possible.
- a ***recce route*** (short for "route reconnaissance") task that causes the UAV to fly a route to a named destination. The sensor payload will be configured to provide reconnaissance information about the flight path, i.e., information about locations of sensor readings that indicate armed vehicles and hostile air defence. If the UAV possesses knowledge about another UAV also tasked with a recce of the same route, it will modify its flight path to maximize sensor coverage.
- a ***recce area*** task that causes the UAV to gather recce information about a named area. The camera will be used to provide ortho-photos of the area.
- an ***object surveillance*** task. While working on this task, the UAV will use the payload control to deliver a continuous video stream of a named location.
- a ***cross corridor*** task makes the UAV fly through a transition corridor between friendly and hostile territory. It consists in avoiding friendly fire and ease cooperation with the own ground based air defence; this crossing is modelled as separate task. Moreover, it is the only task allowed to cross the border between friendly and hostile territory.
- a ***landing*** task causes the UAV to take an approach route to an airfield and to land at that airfield.

The capability to understand these tasks at mission level consists in knowledge of several domains, i.e., artificial situation awareness, planning capabilities and using the air vehicle and its payload. This requires an automation that incorporates certain sub-functions as found in cognitive behaviour of a human [10, 14], i.e., creating cognitive behaviour of the automation. The following sections discuss issues concerning the levels of automation and describe the architecture and information processing of a so-called Artificial Cognitive Unit (ACU).

IV. LEVELS OF AUTOMATION

Currently, UAV systems operate on a wide range of different guidance modes. That modes cover the whole range from direct manual control [20], flight control based [9], scripted behaviours [2] up to above-mentioned task-based guidance [10]. These guidance modes form a stack of *abstraction layers* as depicted in Figure 2. In this figure, “R/C pilot” refers to remotely controlled piloted systems like model airplanes. FMS stands for Flight Management Systems capable of following pre-programmed waypoint lists.

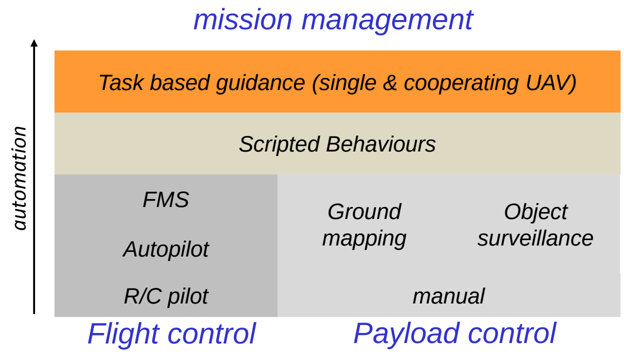

Figure 2. Levels of abstraction in UAV guidance [1]

Sheridan and Verplank [21] describe a different view of levels of automation. These levels are mostly independent from the chosen abstraction layer but set the focus on task allocation and *authority sharing* between the human and the automation. They range from manual control (level 1) to automation that does neither allow intervention from the human operator nor provide information about the action taken (level 10). In the design of current UAV guidance systems, various levels of automation can be found, e.g., in waypoint based guidance systems, the definition of waypoints may be the sole responsibility of the human operator. No automation, in this case, is provided to support that task. However, automatic flight termination systems, e.g., may not allow the human to veto on the decision of the automation but merely report the flight termination after its execution, i.e., level 7 according to Sheridan and Verplank: “computer does the whole job and necessarily tells the human what it did” [21].

Another view to automation focuses on capabilities and the *interoperability* with the control station provided by the system. A prominent example for this kind of automation scale is defined in [22] as *Levels of Interoperability (LoI)*:

- Level 1: Indirect receipt of UAV data
- Level 2: Direct receipt of UAV data
- Level 3: Level 2 plus control and monitoring of the payload
- Level 4: Control and monitoring of the UAV, less launch and recovery
- Level 5: Level 4 plus launch and recovery

The task-based guidance approach described in this paper introduces an additional dimension in the levels of automation. The operator can choose to provide different tasks to the UAV. The UAV will check the tasks for consistency and may insert additional tasks to warrant a consistent task agenda. The consistency check and completion of the task agenda is based on a planning scheme, which behaves deterministic with respect to the current tactical situation and the task elements known so far. Therefore, the operator may choose to specify only task elements relevant to him or her and leave the specification of other tasks to the UAV. This particular type of adaptable automation allows the specification of strict or tight task agendas, i.e., the human operator defines every task of the UAV. However, also loose task agendas may be defined, i.e., the human operator only defines the most important tasks and leaves the details to the UAV. Therefore, this level of automation defines a varying *tightness* of UAV control.

Moreover, this kind of automation also can reduce the chance of human errors, because unintentionally omitted tasks are also completed by the automation.

Table I shows an overview of the aforementioned dimensions of automation in UAV guidance. In the design of a UAV guidance system, each automation level may be fixed, e.g., a system may provide task-based guidance (abstraction) with management where the system offers a complete set of action alternatives, i.e., authority sharing on level 2 [21] including launch and recovery (interoperability LoI 5) where every single task has to be specified by the human operator (strict tightness).

Despite of having a fixed level of automation on the four scales, a system can allow the human operator to adapt the abstraction level, the sharing of authority and the tightness level. Moreover, the automation can change the sharing of authority, i.e., it can be designed as adaptive system.

TABLE I. DIMENSIONS OF AUTOMATION

Dimension	fixed	adaptable	adaptive
Abstraction	•	•	
Authority sharing	•	•	•
Interoperability	•		
Tightness	•	•	

As the focus of this work is on the task-based guidance and the tightness of the UAV guidance, our prototype and evaluation environment uses a fixed abstraction level (task-based guidance), a fixed sharing of authority (depending on the automated function) and operates on LoI 5. The tightness can be implicitly adapted by the human operator. For every task the operator assigns to the UAV the authority of task refinement is passed from the operator to the UAV. The amount of the required refinement defines the degree of tightness in the UAV guidance.

V. SYSTEM ARCHITECTURE

With respect to implementing the desired machine behaviours, this section will provide an overview of the design principles and information processing architecture enabling task-based guidance capabilities.

A. Design of knowledge-based Artificial Cognitive Units

Based on models of cognitive capabilities of human pilots, Artificial Cognitive Units (ACUs) were designed. As depicted in Figure 3, these units become the sole mediator between the human operator and the vehicle [23] in the work system [17]. This additional automation allows the desired shift in the guidance paradigm from the subsystem level, i.e., separate flight guidance and payload management, to commanding intelligent participants in the mission context (also refer to [24]).

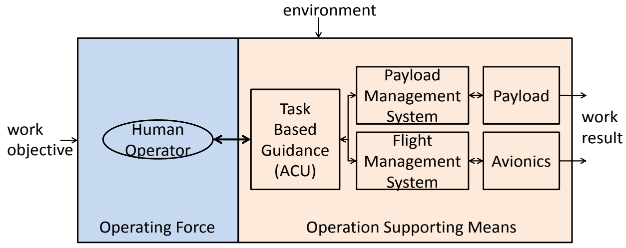

Figure 3. Work system "UAV guidance"

To understand and execute tasks with respect to the current situation, the ACU requires relevant parts of the knowledge and cognitive capabilities of human pilots. That knowledge can be grouped into system management, understanding and evaluating mission objectives in the context of the current scenario as well as knowledge to interact with the human operator [25]. This knowledge is derived by formalization of domain specific procedures defined in documents like the NATO doctrine for helicopter use in land operations [26]. Furthermore, interviews with experienced helicopter pilots revealed relevant knowledge. The interviews and the additional evaluation of recordings of training missions used the Cognitive Process Method [13]. For every phase, the human's objective is evaluated. Moreover, all possible and hypothetic action alternatives to pursue the objective are determined. Furthermore, all environmental knowledge is gathered, which is used to select a particular action alternative or which influences the execution of a chosen action. In our laboratory prototype, this knowledge is used to select a particular action alternative over another, thereby avoiding state space explosions and reducing planning time. At last, the procedural knowledge to execute the actions is evaluated and transformed into machine readable instruction models.

B. Human-machine interface

To support the guidance of multiple UAVs from a manned helicopter, the human-machine interface (HMI) has to be integrated into the manned helicopter. Considering an audio interface, i.e., speech recognition to guide the UAVs, was rejected by a majority of the interviewed pilots due to the already high radio traffic that has to be handled by the helicopter crew.

Therefore, a graphical interface was chosen to interact with the UAV. This interface is integrated into two identical multifunctional displays available to the commander of the manned helicopter. Figure 4 depicts the implemented multifunctional display format.

On the lower left of the multifunctional keyboard, the operator can switch between UAV control and the displays of the manned helicopter (A/C / UAV). Above, the current UAV can be selected. On the top left, the operator can select three different modes: CAM, TASKS, and ID. The right multifunctional soft keyboard shows the context sensitive options for the current mode chosen on the left.

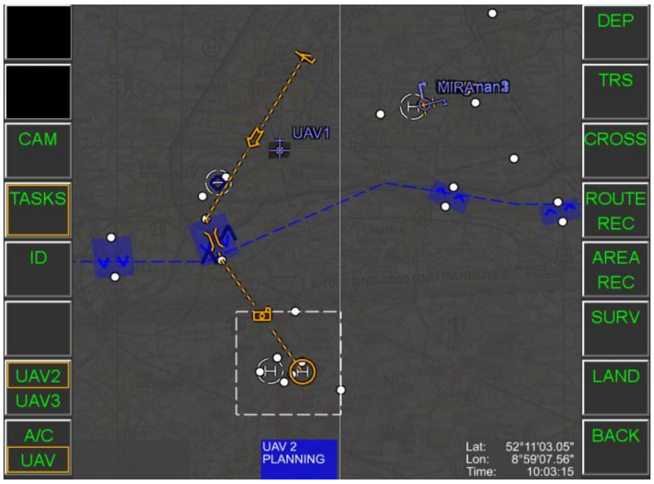

Figure 4. UAV tasking interface

CAM provides a live video stream from the camera of the currently selected UAV.

TASKS can be used to monitor the current tactical situation and to manipulate the displayed task elements of the currently selected UAV. The currently active task is highlighted in yellow. A task can be inserted into the task agenda of the UAV by choosing the task type as shown on the right in Figure 4, optionally choosing the predecessor of the task on the map and selecting the target position of the task. A task can be selected for immediate execution. This functionality can be used to start the execution of the first task as well as for skipping tasks, i.e., the human operator chooses to cancel one or more task to give priority to a more important task. Additionally, tasks can be deleted and moved, i.e., the target area description of the task is altered. If tasks are added, deleted or modified, the UAV will maintain a consistent task agenda by inserting missing tasks depending on the current tactical situation. As long as this planning is in progress, it is indicated on the bottom of the display as shown for UAV number 2 in Figure 4. To prevent immediate re-insertion of deleted task elements, the consistency checks are delayed after the operator deletes a task element. This allows further modifications of the task agenda by the human operator without being interrupted by the UAV.

The ID display mode is used to review photos taken by the UAV and to classify the objects on the images into pre-defined types (car, military vehicle, ground based air defence) and hostility, i.e., neutral, friend or foe. Those classifications are also reflected in the tactical situation shown in the task mode as well as the electronic map displays available to the pilot flying. Furthermore, those classifications will be transmitted to the UAVs in order to support reaction to the changed tactical environment, e.g., to plan flight routes around hostile air defence.

The combination of those display functionalities shall allow the human operator to guide the UAVs to support a military air assault mission that involves operation over hostile areas and support of infantry troops. Moreover, by tasking the UAVs using mission terms, e.g., by selection of "area reconnaissance of the primary landing site", the control of three UAVs shall be feasible and enhance mission safety by providing valuable information about mission relevant areas and routes without risking exposure of own troops to threats like ground based air defence and other opposing forces.

C. Information processing

The implementation of artificial cognitive units is based on the Cognitive System Architecture (COSA) framework [13]. This framework is based upon Soar [28] and adds support for object-oriented programming as well as stereotypes for structuring the knowledge into environment models, desires, action alternatives and instruction models.

This (a-priori) knowledge constitutes the application specific part of the Cognitive Process, which is described in detail by Putzer and Onken [13] as well as Onken and Schulte [17]. Information and knowledge processing as well as interfacing with the environment is depicted in Figure 5. The inner ellipse represents the static, a-priori knowledge of the system. This knowledge is defined at design-time. Input data and instances of the a-priori knowledge constitute the situation knowledge, which is depicted in light grey in Figure 5. The arrows indicate the information flow in the cognitive process. Every processing step modifies one specific area of situation knowledge, but may read from all areas of knowledge.

The following describes the information processing steps using examples of the knowledge of the UAVs' on-board ACUs.

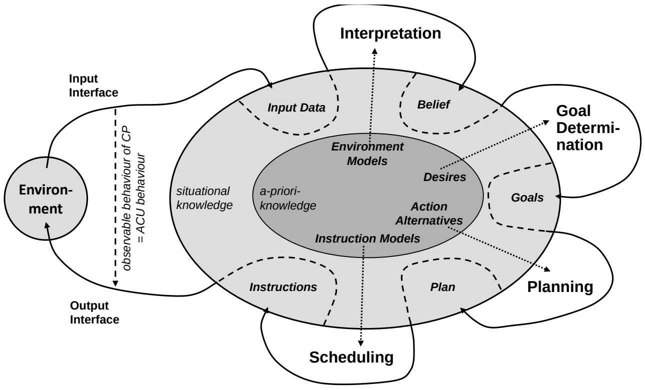

Figure 5. Knowledge processing in the Cognitive Process [17]

Input data are retrieved from the environment by input interfaces. There are three types of input interfaces: (1) reading sensor information from the sensors of the UAV, (2) reading information from the communication link of the UAV and (3) providing results from on-board automation, e.g., information about flight routes generated by an external route planner.

The *environment models* of the a-priori knowledge of the ACU drive the interpretation of input data into instances of semantic concepts. Those concepts form an understanding of the current tactical environment including knowledge about existence and positions of threats, areas, bases, landing sites, routes, waypoints etc. Due to the nature of the cognitive system architecture, environment models continuously monitor all the input data and other knowledge of the cognitive process and react with instantiation, modification or removal of corresponding beliefs. All instances of environment models, i.e., *beliefs*, form the representation of the current situation of the UAV. *Desires* describe world states the UAV should maintain. Every desire contains declarative knowledge about the detection of violation of the state, i.e., it contains rules that continuously monitor the situation for facts that indicate a violation of the desire. If a violation is detected, an instance of the desire is created, i.e., the desire creates an active goal. Desires may contain knowledge that derives priorities from the current situation, e.g., the desire of executing task modifications issued by the human operator takes precedence over the desire of having a consistent task agenda. The motivation is to avoid fixing agendas that are currently modified by the operator.

Action alternatives provide ways to support active goals. They instantiate if a corresponding goal is active, but only if the current situational knowledge allows the selection of the action alternative. If more than one action alternative can be proposed, then the action alternatives model selection knowledge to prefer one alternative over the other. For example, the action alternatives "transit flight" and "route reconnaissance" may both support the goal of reaching a specific location. If both action alternatives are feasible, the fitness and selection of the alternative depends on the type of area that has to be crossed.

After the action alternative has been chosen, the *instruction models* become active and support the action alternatives by generating instructions on the output interface of the ACU. Those instructions are read by the output interface and cause the transmission of radio messages, configuration changes at the flight control system or the payload system or activate on-board automation, e.g., a route planner.

In combination, all those processing steps depicted in Figure 5 generate purely goal-driven behaviour that allows reasoning over the tactical situation and the task elements entered by the human operator to provide situation-dependent actions, which are consistent with tactical concepts of operations. Unlike procedure-based architectures, the Cognitive Process is not bound to pre-defined algorithms, which are affected by unforeseen changes in the environment or may be unable to deal with concurrent events.. Instead, the situation is continuously analysed with respect to explicitly encoded domain knowledge. Furthermore, the open world assumption of COSA allows dealing with "… incomplete information, which is essential taking sensor data into account." [27].

D. Knowledge Base

While the information processing of COSA is domain independent, the knowledge base defines the domain knowledge models. The knowledge of the ACU is grouped into packages which may refer to each other. Each package defines knowledge of one subdomain:

- environment
- supervisory control
- mission
- cooperation
- task synthesis for loose vs. tight control
- task scheduling
- role management

Every package consists of knowledge models, which are represented in CPL (Cognitive Programming Language) [25], which is based on Soar [28]. For every type of knowledge described in this section, there is a separate knowledge model encoded in CPL.

The knowledge models of the prototype focus on mission management, cooperation of UAVs and task-based guidance in general and are mostly vehicle independent. However, [24] presents an architecture that allows the integration of high-level UAV mission tasking and vehicle specific knowledge.

1) *Environment knowledge*

The environment package contains all knowledge models that allow the ACU to build an internal, symbolic representation of the current environment including the state of the UAV. This knowledge may be considered machine situation awareness comparable to human situation awareness on level 2 (understanding of the current situation) according to Endsley [29].

This knowledge covers models about the existence of the UAV and other UAVs in the team. Moreover, knowledge about ground forces, air spaces, positions in general and relation between positions is represented. Information about the sensor system is covered by a model of the on-board sensors. Information about sensor photos that may be reviewed by the human operator for classification is represented by a corresponding knowledge model.

```
class <belief> hotspot
{
  attributes:
    string name := |hotspot|;

    // location of the hotspot (WGS84)
    double lat;
    double lon;
    double alt;

  behaviour:
    sp { create*from-sensor-input
    : o-support
      (state <s> ^io.input-link.sensor.thermal-detector <sensinput>)
      (<sensinput> ^lat <lat> ^lon <lon> ^alt <alt> )
    -->
      (elaborate <i>)
      (<i> ^lat <lat> ^lon <lon> ^alt <alt> )
  }
};
```

Figure 6. Example of an environment model

Fig. 6 shows a short example of an environment model of the UAV. This particular environment model represents sensor readings of the automated target recognition system (ATR), which indicate possible threats at a defined position. The stereotype “belief” makes the knowledge model an environment model. The behavior “create*from-sensor-input” consists of a condition part and an action part. The conditions are matched against the current knowledge and check for the existence of a “thermal-detector” node in the sensor input data. If the condition is met, an instance of the knowledge model is created (“elaborate”) and the coordinates of the sensor input are copied from the input data into the newly created instance. The keyword “o-support” makes the instance permanent, i.e., the general truth maintenance property of COSA is not applied and the instance will not disappear if the input data disappears. The syntax used here is an object oriented extension [13] of Soar [28].

2) *Supervisory control knowledge*

Knowledge about supervisory control covers knowledge necessary for the task assignment to the UAV. It contains a model of the instruction sent from the human operator to the UAV. For every task type available, there is an instruction model derived from that base instruction model. Furthermore, there are models for the messages that request the execution of a specific task as well as one model for the request to stop or delete a task.

Another knowledge model in this package represents the current guidance mode of the UAV. This model is responsible for the representation of the task-based guidance as such. It detects overrides to the task-based guidance, e.g., the aforementioned request to stop a task, and is responsible for granting or revoking access to the flight management system to the ACU as such. The ACU always initializes with those privileges being revoked, i.e., it is the sole authority of the human operator to transfer the authority over the flight management system to the ACU.

3) *Mission knowledge*

The mission knowledge represents the models used to execute the tasks assigned to the ACU. Most of the behavior of the ACU is defined by its desire to comply with the assigned tasks. This knowledge model makes the ACU strive to fulfill the current task at hand.

Furthermore, the mission knowledge contains the desire to use opportunities for retrieving additional recce information which may be unrelated to the current task. Therefore, the ACU combines its knowledge about the type of sensor information, i.e., “unidentified sensor-hotspot”, the availability of its sensors, the availability of sensor information from its own sensors and from other UAVs, and its relative position to the unidentified force. This combination of knowledge enables the UAV to safely detect and use the chance of getting more information about the location. Moreover, the UAVs also behave cooperative as the decision to generate additional sensor information is suppressed if another UAV has generated that sensor information from a similar angle to the unidentified force.

The action alternatives of this knowledge package model ways to achieve active goals. Moreover, additional desires model prerequisites for action alternatives, e.g., to make the action alternative of crossing an airspace corridor feasible, the aircraft shall be near the entry point of the airspace corridor.

Instruction models contain the knowledge about how to execute the chosen action alternative, i.e., how to interact with the on-board automation and the environment.

4) *Cooperation knowledge*

The cooperation package contains all models which

- represent knowledge about current and future tasks of the own UAV as well as tasks of other UAVs.
- represent knowledge about the task at hand and the sequence of future tasks. This knowledge also includes strategies for determining the current task at hand.
- determine the information needs of all teammates, i.e., other UAVs, and generates the information feedback to the human operator. Furthermore, action alternatives exist to fulfill those information needs.

There is a common base model for all task elements that defines the common knowledge and common behavior of all tasks. Derived from that model, there is a model for every task type available, i.e.:

- *recce-route* is the task to get reconnaissance information about a flight route to a specified destination.
- *recce-area* is the task to get information about a specified area and its surroundings.
- *surveillance* delivers a continuous video stream of a specified location or a designated force.
- *transit* is the task to fly a safe transit to a specified target location.
- *departure* is the task to execute a departure procedure with compliance to the departure rules of the current location.
- *landing* is the task to execute an approach and landing procedure with compliance to the approach rules of the specified landing location.
- *cross-flot* is the task to cross airspace boundaries, i.e., the so-called forward line of own troops (FLOT), at a specified airspace corridor.

An *agenda* models the sequence of the tasks of a UAV. In order to know the current task at hand, the cooperation package defines three action alternatives. First, if there is an instruction from the human operator requesting a task for immediate execution, then this task becomes the current task. If this alternative is available, then it is preferred over other strategies. Second, the ACU may select the successor of the last completed task as the new current task. This is the default strategy. If neither strategy is applicable, the ACU may choose the first non-completed task from the agenda.

To model the information needs of the team mates, a *knowledge monitor* tracks instantiation, change and destruction of relevant knowledge models. The relevance for team mates is implemented as additional model attribute that can be evaluated at runtime. The model of the desire to keep the team informed is activated, if an instance of "knowledge monitor" detects a change in the monitored instances. As a consequence, action alternatives are activated and propose to communicate the change in the knowledge to the team. There are multiple action alternatives to model different serializations of knowledge, i.e., to address different communication channels.

5) Knowledge about task synthesis

To model the variable tightness described in Section IV, the ACU possesses a desire to *have a consistent task agenda*. This desire activates into an active goal, if one of the following rules for consistent agendas is violated:

1. Every task except departure requires the UAV to be airborne.
2. If there is an approach route for a landing site, then it shall be used by the landing task.
3. The tasks "recce-area" and "surveillance" require the UAV to be near the area or the named location respectively.
4. The task "cross-flot" should start at an airspace corridor.
5. If there are designated entry/exit points for an operation area, then these shall be used by the UAV.
6. If there are airspace corridors connecting airspaces, then those corridors shall be used.

To detect those violations, there is a knowledge model representing the state of the UAV *after completion* of a task. An additional instance of that knowledge model refers to the *current state* of the UAV. Furthermore, there is a knowledge model whose instances represent the preconditions of *future tasks*. Violations of the rules can be detected by comparing the prerequisites of one task with the predicted state after completion of its predecessor.

An example of a violation is depicted in Figure 4. The route reconnaissance on the lower half of the image, which is shown by a stippled, orange line with a camera symbol, crosses the boundaries of the operation area (white stippled rectangle). However, that area shall be entered only via its designated entry points (white dots). Therefore, this leads to an activation of "have a consistent task agenda". As this activation is considered relevant knowledge to the team, it is transmitted to the operator and shown as "UAV planning" in Figure 4.

If there are multiple, concurrent violations of rules, the violations are scheduled according to a "divide-and-conquer" scheme, e.g., if rule 6 is violated, this violation is addressed first to divide the agenda into parts operating only in a single airspace.

The action alternatives supporting the goal of having a consistent agenda are the creation and insertion of additional tasks into the task agenda. Furthermore, existing tasks may be altered, e.g., to ensure that a cross-flot task starts on the right side of the airspace corridor. Action alternatives are selected based on the current or projected tactical situation, e.g., the resolution of a violation of rule 4 depends on the type of the terrain, i.e. a "transit" task is inserted when operating over safe terrain and a "recce route" task is inserted to reach the corridor while operating over unsafe terrain.

As mentioned in Section IV, the human operator can make use of this behaviour of the ACU by skipping tasks on purpose and thereby shifting the completion and specification of missing tasks to the ACU.

6) Task scheduling

The human machine interface allows the operator to insert new tasks at a certain position of the agenda after having specified the predecessor of the new task. However, the operator may also define tasks without specifying where to insert the task into the existing agenda. Therefore, the ACU follows a desire to know the task insertion point. For new tasks without specified insertion point that the behavior of that desire creates an active goal.

The action alternatives for determining the insertion point are to insert the task at the end of the task agenda or to insert the task in a way that minimizes the detour based on the existing task agenda. The latter alternative is not available for departures and landings.

7) Role management

Knowledge about role management supports the cooperation of multiple actors (UAVs) working on a common task. The term role is used as defined in social sciences [30]. Biddle states that roles in the symbolic interactionist role theory are *"…thought to reflect norms, attitudes, contextual demands, negotiation, and the evolving definition of the situation as understood by the actors."* [30]

To bring the concept of roles to the UAV, the ACU has a knowledge model describing its roles and the roles of the teammates. Furthermore, another knowledge model defines the desire of *having a unique role per task*. This desire is activated into an active goal if there is no role assigned to a task or if there is knowledge available, that the assigned role is also assigned to a teammate for the same task.

There are models about role configurations that define which roles are available depending on the task type and the number of UAVs working on the common task. Depending on those configurations, all possible roles are proposed for a task.

To support the goal of having a unique role per task, there are two action alternatives available. Firstly, the ACU may assign an available role to the common task. The selection can be random or based on the application of selection knowledge like preferring to stick to a role in subsequent tasks of the same type. Secondly, the ACU may drop an assigned role as result of a role conflict.

Therefore, the general outline of role-based cooperation is:

1. UAVs communicate assigned tasks to each other.
2. Each UAV detects that it participates in a task also assigned to another UAV, i.e., a common task requiring cooperation.
3. Every UAV proposes a role describing how to participate in the task.
4. Conflicting and missing role assignments are detected and resolved.
5. Roles affect the way a task is executed by the UAV.

Because of the knowledge-based nature of the ACU, the arbitration of roles is immune to race conditions like simultaneously changing roles and environment. Any invalid role assignment triggers the activation of the goal of having a valid assignment and consequently causes the correction of the role configuration. The following example illustrates how a team of UAVs benefits from this property in a dynamic situation.

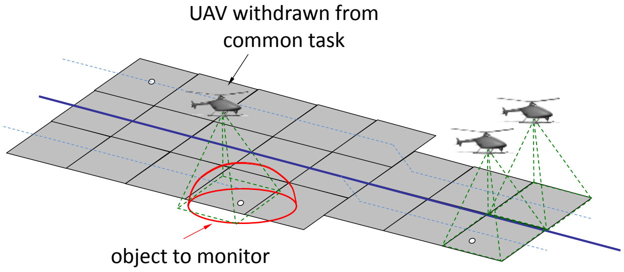

Figure 7. Multiple UAVs working on common task

If there are three UAVs with a common recce-route task, the corresponding role configuration and roles will become active and propose the roles to “fly to the left of the track”, “fly to the right of the track” and “fly on track” in order to maximize the sensor coverage. When the ACU plans its route for the route reconnaissance, the assigned role affects the instruction model responsible for the route planning. Therefore, the route planner is instructed to add an offset to the track while planning. This leads to a formation-like flight of the three UAVs. The left half of Figure 7 depicts the resulting flight paths of three UAVs flying a common recce-route task. The grey patches illustrate the coverage of the sensor images taken by the UAVs.

Once a UAV is withdrawn from the common task, the roles available may change. This leads to a reassignment of the roles and to a change in the task execution as depicted in the right half of Figure 7, i.e., one UAV is being withdrawn from the common task causing the other UAVs to change their roles and flight paths.

VI. Experimental Setup and Results

Experiments were conducted with experienced German Army helicopter pilots in order to evaluate the task-based guidance approach. The simulator cockpit shown in Figure 1 has been used to perform military transport helicopter missions. The simulation of the UAVs consists of a simple kinematic model of a generic helicopter. The elementary flight performance envelope of this model is comparable to the model of the manned helicopter, i.e., the maximum speed is about 120 knots. However, the concept of task-based UAV guidance is independent from specific UAV platform types or dynamics, and is also applicable to fixed-wing aircraft. The kinematic flight model was fitted with an autopilot, waypoint tracking capabilities, and interfaces to the ACU. Together with an electro-optical sensor simulation, this simulates the flight control and payload control as depicted in Figure 2. In the simulation setup, the LoI is fixed at level 5, i.e., the operator has full control of UAV including payload, launch and recovery (cf. Section IV) and only the task-based layer is available to the human operator, i.e., the abstraction layer is fixed in the experiment.

The objective of the missions was to pick up troops from a known location and to carry them to a possibly threatened destination. According to the briefing, three UAVs should be used to provide reconnaissance information about the flight routes and landing sites in order to minimize exposure of the manned helicopter to threats. In addition to the tasks to perform in previous baseline experiments without task-based guidance [9], in this experiment an unscheduled combat recovery task was commanded to the crew as soon as the main mission objective had been accomplished.

Prior to the measurements, every test person had been given one and a half day of education and training on the system. The test persons acted as pilot flying and commander. This configuration was chosen to evaluate the effects of the UAV guidance to crew cooperation and crew resource management.

The following data were recorded during the experiment:

- Interaction of the operator with the system
- Commands sent to the UAV via data link
- Resulting task agendas of the UAVs
- Helicopter and UAV flight paths
- Sensor coverage

This data was used to retrieve measures in the categories *performance*, *behaviour* and *subjective ratings*. Performance covers the mission success as such, including different aspects of reconnaissance and UAV flight guidance. Behavioural measures include the attention demand of UAV guidance, the distribution of interaction with the UAV guidance system over the mission phases and the tightness of the UAV guidance (see Section IV). Subjective ratings cover the perceived workload and the system ratings from the test persons.

In the following, the measures and results of the commander of the manned helicopter, who is also the UAV operator at the same time, are presented. Results for the complete flight crew may be found in [31].

A. Performance

One key aspect when measuring performance in military missions is the overall mission success. The test persons managed to accomplish the mission including the additional combat recovery in every simulation run.

Another figure is the gain in mission safety and security achieved by the deployment of detached sensor platforms. This can be estimated by the sensor coverage of the flight path of the manned helicopter. In the experiment, the manned helicopter operated within the terrain mapped by ortho-photos 94.5% of the time in hostile areas.

It is the responsibility of the commander to use the UAVs in a way that maximizes tactical advantages. According to the test persons, this consisted in having sufficient information about the flight path of the helicopter to support mission-critical decisions. Moreover, the army aviators emphasized the importance of having forces near the helicopter to react to unforeseen events.

To evaluate the tactical advantages, a scoring was developed to measure the quality of the reconnaissance achieved with the UAVs.

TABLE II. SCORES FOR RECONNAISSANCE PERFORMANCE

	yes	*no*
Reconnaissance data of helicopter route available in time?	2	0
Reconnaissance data of primary landing site available in time?	2	0
Classification of UAV sensor data in time? (only 1 point, if pilot flying had to request classification)	2	0

Table II lists the applied criteria for the reconnaissance performance and the corresponding scoring. The video recordings of the simulations were analysed to apply the conditions listed. To get the full score of 2 points, the listed requirement has always to be fulfilled during the mission. Otherwise, the criterion was assessed 0 points. The availability of reconnaissance data was considered not “in time”, if the manned helicopter had to slow down in order to wait for UAV data or classification or if the helicopter operated near unknown or not-located forces. In the experiment, an average score of 88.3% (n=16) of the maximum of 6 points was reached.

Furthermore, most of the commanders used the capabilities of the UAVs to get reconnaissance information that could have been useful in alternate outcomes of the missions, i.e., information about alternate flight routes and information about alternate landing sites. In some cases this led to delays in the mission progress as UAVs were busy getting information of alternate routes and landing sites.

TABLE III. SCORES FOR ADDITIONAL TACTICAL BENEFITS

	yes	*partial*	*no*
Reconnaissance data of alternate flight routes available?	2	1	0
Reconnaissance data of alternate landing sites available?	2	1	0
Delays in the mission progress because of missing reconnaissance data?	0	n/a	2

Table III provides a scoring for these additional benefits, the commanders got from the deployment of the UAVs. On average (n=16), 60.5% of the maximum score was reached in this scale.

The results in this section indicate, that task-based guidance is a way of UAV guidance which supports the overall mission success as well as mission safety. Moreover, the test persons used the UAVs as force multiplier to get additional sensor data of alternate sites and routes.

B. Fan-Out

Supervision of the UAVs places extra work demands on the human operator. To get a measure of the demands of multiple UAV guidance using task-based guidance, the maximum number of UAVs the operator can handle shall be estimated. This estimation is based on the operator’s attention required by one UAV. Goodrich and Olsen [32] introduce the concept of Robot Attention Demand (RAD) which can be calculated as

$$\mathrm{RAD} = \frac{\mathrm{IT}}{\mathrm{IT+NT}} \tag{1}$$

where IT denotes the Interaction Time, i.e., the time the operator actually interacts with a multi-robot system. NT is the Neglect Time, i.e., the amount of time a robot can be neglected before its performance drops below a certain threshold [32].

For multi-robot systems like multi-UAV guidance, it can be assumed, that the human operator uses NT to interact with additional robots. Therefore, the inverse of RAD gives an upper bound for the number of robots that the human operator can handle. This measure is called Fan-Out (FO) [32].

To further improve the estimate of the Fan-Out, Cummings et al. [33, 34] introduce the concept of Wait Time (WT). Wait times occur, if the human operator should interact with a robot, but fails to do so because he is busy with another robot (wait time caused by interaction – WTI), because of task switching delays (wait time in decision making queue – WTQ) or he lacks the situation awareness to recognize the need for interaction (WTSA). With wait times, the Fan-Out can be calculated as

$$\mathrm{FO} = \frac{\mathrm{NT}}{\mathrm{IT+WT}} + 1 \tag{2}$$

To apply the measurement of IT, NT and WT to the experiment, which models a complex military scenario, the following criteria are used to distinguish interaction time, neglect time and wait time:

Wait Time (WT) occurs in the following cases:

- At least one UAV is idle, i.e., it has completed all of its tasks.

- There is at least one mission relevant object in the sensor images of the UAV waiting for classification by the human operator, e.g., a UAV has taken an image of hostile ground forces but the operator has not yet evaluated that image.
- A UAV enters the range of hostile air defence.

Interaction Time (IT) occurs, if none of the conditions for wait times are fulfilled and at least one of the following conditions is true:

- The operator prepares the human-machine interface for interacting with a UAV.
- The operator defines, modifies or removes a task of a UAV.
- The operator evaluates UAV sensor data or prepares the human-machine interface to do so.
- The operator interacts with the human-machine interface to monitor the current position and task of a UAV. This is equivalent to “robot monitoring and selection” as defined by Olsen [35].

All other time spans are considered Neglect Time (NT).

The times were measured by evaluating the interactions of the operator with the overall system instead of measuring per UAV. Therefore, the resulting Fan-Out is relative to the initial number of UAVs, which is three.

The average neglect time measured is 57% (n=16) of the overall mission time. The mean of the wait times is 6.5% (n=16).

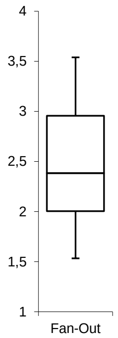

Figure 8. Distribution of the Fan-Out (FO) in the experiment

Hence, the average Fan-Out is computed to 2.49 (n=16).

The average share of NT used for interactions with the systems of the manned helicopter as well as interacting with the pilot flying is only 19%.

This result and the high neglect time indicate that task-based guidance of three UAVs is feasible and the human operator still has sufficient resources to remain in his role of being the mission commander and pilot in command of the manned helicopter.

C. Task Instructions per Mission Phase

To evaluate if the concept of task-based guidance is also applicable in situations unforeseen by the human operator, all missions of the experiment were divided into four phases:

- Phase A begins with the start of the experiment and ends with the take-off of the manned helicopter. This phase is not time-critical, i.e., it is assumed that the crew can start the preparation of the mission as early as required, although in the real application there might be some organisational and military constraints to that.
- Phase B begins with the take-off of the manned helicopter and ends with the successful completion of the main mission objective, e.g., if the main mission objective is to transport troops, phase B ends when the troops leave the helicopter at the remote landing site.
- Phase C starts after phase B with the assignment of an additional mission objective which was unknown to the crew prior to the experiment, e.g., to rescue the crew of a crashed aircraft. Phase C ends with the successful completion of the additional mission assignment.
- Phase D starts after phase C and covers the egress to the home base.

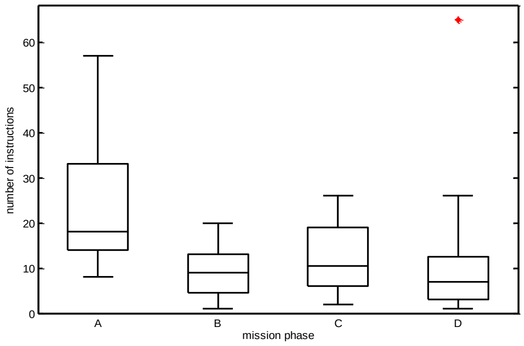

Figure 9. Number of task modifications per mission phase

Figure 9 depicts the number of task instructions, i.e., instructions to insert, alter or remove tasks from the agenda, issued by the operator per mission phase. The mission phase with the most instructions to the UAVs was the time-wise uncritical preparation phase A. If there are only minor changes to the situation, i.e., changes that can be foreseen by experienced mission commanders, only a small number of changes to the UAV task agenda are necessary (phases B and D in Figure 9).

However, if there is a fundamental change to the mission objective including locations and goals which were unknown to the helicopter crew, this can also be handled with a relative small number of changes to the UAV agenda. This is expressed by a small increase of tasking instructions in phase C compared with phases B and D.

Therefore, task-based guidance as evaluated in this experiment shows two qualities:

1. It allows the human operator to shift interactions from mission critical phases to the mission preparation.
2. Even unforeseen situations can be handled with an adequate amount of interactions that is not significantly larger than the number of interactions in known situations.

Just like in conventional, pre-planned missions with only little flexible mission management approaches, most of the interactions are performed in the planning and preparation phase. Nevertheless, the flexibility of the task-based guidance approach is demonstrated, because the unknown secondary task and, hence, the required re-planning activities could be handled with minimum effort.

D. Tightness Level

The tightness level in the task-based UAV guidance can be expressed as the ratio of the number of task elements assigned by the human operator versus the number of synthesized tasks.

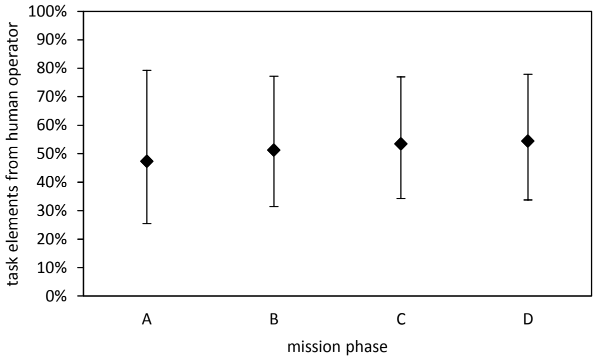

Figure 10. Average thightness in UAV guidance per mission phase

In the experiment, 51% (n=8) of the elements in the task agendas of the UAVs were inserted by the human operator. The remaining 49% of the task elements were automatically inserted by the UAVs to establish a consistent task agenda. Figure 10 depicts the share of task elements assigned by the human operator. In the experiment, this observed tightness level is mostly independent from the mission phase. However, it may vary depending on the individual human operator, as depicted in Figure 11 which shows the figures for two different operators.

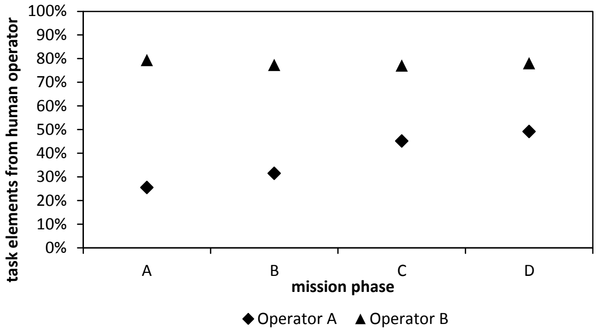

Figure 11. Individual tightness in UAV guidance

Operator A preferred to allow the UAV a higher degree of authority and defined only 38% of all task elements entries during the mission. While being faced with an unknown situation (phase C), the operator took back some of the authority by specifying the new tasks in more detail.

Operator B specified 78% of all tasks elements and did not change that tight guidance level during the course of the mission.

E. Subjective Measures

In every simulation run, the simulation had been halted twice, i.e., in the ingress and during a demanding situation while the helicopter is near the hostile target area, to get measures of the operator's workload using NASA TLX [36]. During the simulation halt, all displays and the virtual pilot view were blanked and the intercom between pilot flying and pilot non-flying was disabled. To get an indication of the test persons' situation awareness, the test persons were simultaneously questioned about the current tactical situations, system settings, e.g., radio configuration, and the upcoming tasks of the UAV and the manned helicopter. Furthermore, commander and pilot had to mark the positions of the manned helicopter, the UAVs and known ground forces in an electronic map. The specified positions were compared with the actual positions of the objects. This measure is an adaption of the SAGAT technique [29]. The test persons achieved a score of 100% for deviations less than 0.75 nm, 50% for deviations up to 1.5 nm and 0% for larger distances or if the object was missing. Only hostile ground forces objects were counted, because neutral ground forces are considered irrelevant to the mission progress [31].

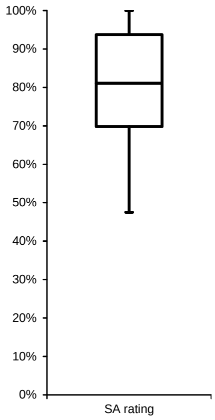

Figure 12. Overall SAGAT measures

Figure 12 depicts the distribution of this score. The commanders got an average score of 80% in this test.

After every mission, a debriefing follows which includes questions about the system acceptance, system handling, interface handling as well as feedback about the degree of realism of the simulation environment.

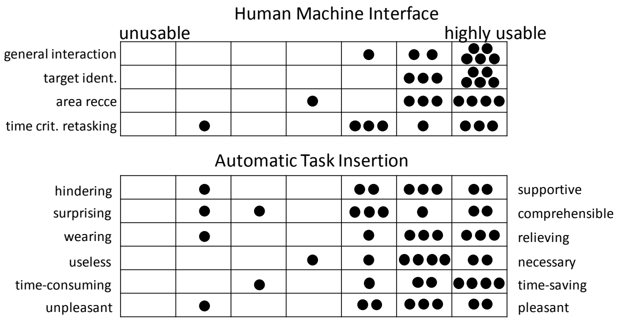

Figure 13. Subjective Pilot Ratings for HMI / Consistency Management

Figure 13 shows the subjective ratings of the test persons concerning the human machine interface and the automatic maintenance of a consistent task agenda, i.e., the automatic insertion of tasks. The representation of tasks as graphic elements on an interactive map was considered suitable for task monitoring and task manipulation. As depicted in Figure 13, one operator missed interfaces for time critical modification of tasks, especially a way to quickly assign low-level commands, e.g., heading and speed, to the UAV. The chosen type of human-machine interface and the automatic insertion of task elements to maintain a consistent agenda are generally accepted by all test persons.

The test persons stated that handling the UAVs consumed an average of 62% of the time while 34% remained for acting as commander of the manned helicopter. This indicates that the test persons felt the UAV guidance twice as demanding as supporting the pilot flying. However, the test persons also experienced the UAVs as highly supportive element for mission accomplishment, which outweighs the additional demands of guiding the unmanned aircraft.

TLX measures of the commander range from 23% of subjective workload during the ingress over friendly territory up to a value of 60% during time-critical re-planning of multiple UAV in the target area.

VII. Conclusion

This paper shows a way how operational knowledge can be encoded into an artificial cognitive system to allow the guidance of multiple UAV from the commander of manned helicopter. Task-based guidance, being the guidance concept advertised in this paper, shows high potential for embedding unmanned assets not just as additional complex automation but as artificial subordinates.

The experiment provided evidence, that task-based guided UAVs can increase the overall mission performance and provide tactical advantages. The behavioural measures show that task-based guidance consumes only a moderate share of the operator's mental resources, which allows him to remain in his role of the commander of the manned helicopter. Furthermore, the introduced adaptable tightness of UAV control is found to be intuitively used by the operators to balance the authority between the human and the UAV.

Subjective measures and ratings indicated a manageable workload, a sufficient level of situation awareness as well as a good acceptance of task-based guidance.

Fields that shall be addressed in future work are the handover and shared use of UAV capabilities. Thereby, UAVs could remain airborne over the operation area and human crews can request UAV services on demand. Furthermore, as reaction to emergencies, the human operator should use varying levels of automation, e.g., bypassing task-based guidance to directly set heading and altitude of a UAV. For that case, a methodology shall be developed that defines when and how the authority over the UAV can be reassigned to the artificial cognitive unit. The introduction of varying levels of automation may also incorporate the guidance of teams of UAVs [37], i.e., a single task can be assigned to multiple unmanned systems and those will define and distribute subtasks within the team.

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