Human-UAV Co-operation Based on Artificial Cognition

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Abstract. In the future, Uninhabited Aerial Vehicles (UAVs) will be part of both civil and military aviation. This includes co-operative mission accomplishment of manned and unmanned assets with little manpower being available for UAV guidance. So, UAVs need to be able to accomplish tasks with a minimum of human intervention and possibly in co-operation with other UAVs or manned aircraft. This paper presents artificial cognition as approach to co-operative capabilities of UAVs. They are guided by so-called Artificial Cognitive Units (ACUs) being capable of goal-directed behavior on the basis of understanding the current situation. Prototype evaluation results show the capability of suchlike co-operative ACUs to yield human-like rationality and the ability to act as peers in a human-ACU team.

Keywords: cognitive automation, artificial cognition, multiple UAV guidance, human-machine co-operation, UAV co-operation.

1 Introduction

In manned aircraft, human pilots are responsible for safe mission accomplishment and have the authority to do whatever is necessary within their scope of allowed action alternatives. This includes managing the automation available onboard. Especially in situations which could not be foreseen during system design and thus cannot be considered when planning a mission, typical human abilities are essential to maximize mission success. Humans are capable of understanding what is going on, reflecting on what should be achieved next and planning the next steps. This human strength can even be assumed in situations the concrete configuration of which could not be anticipated or has never been encountered before.

When considering UAVs which are supposed to fulfill whatever kind of mission, unforeseen situations are likely to occur and have to be handled appropriately. Therefore, human operators still have to be kept in the loop. In this case, a UAV operator acts similar to a remote pilot, being connected to the vehicle via data link rather than being located in the aircraft. However, this approach hits its limitations when e.g. time delays or data link losses occur. Moreover, the guidance of multiple UAVs with limited abilities by one human operator will probably exceed the available human resources in certain situations and result in excessive workload. Finally, for co-operative missions in which teams of unmanned and manned assets work together, the timely coordination can hardly be realized with remotely operated UAVs.

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Our approach to enable multi-UAV guidance and manned-unmanned teaming is to introduce so-called Artificial Cognitive Units (ACUs) aboard the UAVs, which are capable of understanding mission objectives and the environmental situation, which have an explicit representation of goals that should be achieved in the course of a mission and which are able to plan appropriate action sequences. In short, these ACUs mimic certain aspects of human cognition, which are relevant for goal-directed, rational behavior. This is assumed to be a crucial competence to enable human-machine co-operation on peer level and to form manned-unmanned teams in airborne missions.

This paper considers the development, implementation, and evaluation of ACUs for UAV guidance within such manned-unmanned teaming scenarios, in which human pilots have to work together with several co-operative ACUs onboard UAVs in order to successfully accomplish a mission. Within our work, a military air-to-ground attack mission served as an example (see figure 1).

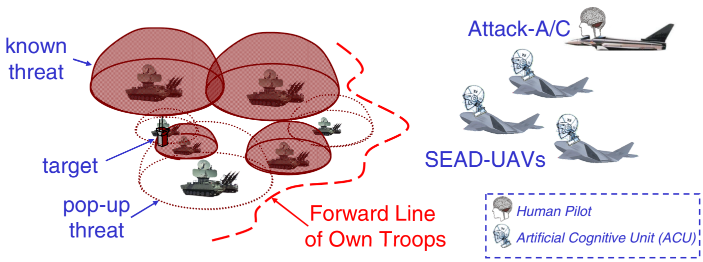

Fig. 1. Generic Air-to-Ground-Attack Scenario for investigation of human-ACU co-operation (A/C: aircraft, SEAD: Suppression of Enemy Air Defense)

To start with, a short introduction on artificial cognition will be given. This includes details on aspects of cognition that are being modeled and realized as technical systems. Afterwards, our concept of knowledge-based co-operation, necessary knowledge and a prototype implementation will be described. Finally, the evaluation of the implemented ACU with respect to goal-oriented behavior and human-machine co-operation will be presented.

2 Artificial Cognition

As mentioned above, we introduce so-called Artificial Cognitive Units (ACUs) aboard UAVs which are capable of goal-directed planning of their behavior while considering the current situation. In order to perform well in as many situational configurations as possible these ACUs have to be able to exhibit behavior on all levels of human performance as introduced by [1]:

- *Skill-based behavior* is characterized by highly automated and efficient execution of sensori-motor patterns without the need to be aware of. Just like an experienced helicopter pilot can perform a hovering task on this level, a controller stabilizing an airborne platform would exhibit the equivalent of skill-based behavior.
- *Rule-based behavior* in contrast requires attentional resources from humans and can be observed in standard task situations. Then, a direct situation-task-mapping

takes place and the appropriate tasks can be executed by means of skill-based capabilities. Typical rule-based behavior in the aviation domain can be observed when processing check lists e.g. before departure.

– *Knowledge-based behavior* is of importance in situations, which have not been experienced before and for which it is not known what should be done next. For example, a pilot might not immediately have an appropriate solution to a situation in which certain mission relevant tasks have to be completed but at the same time unexpected events such as a change of the tactical situation or onboard available resources occur. In order to determine the next steps, at first, the situation has to be understood, then, currently relevant goals will be determined and finally, appropriate actions have to be planned which are suited to achieve the desired state.

While skill-based and rule-based behavior can be implemented into technical systems quite straightforward, performance on the knowledge-based level is much harder to realize, because developers have to enable the system to understand the situation, to reason about super ordinate goals, to decide what to achieve next and to plan appropriate action sequences.

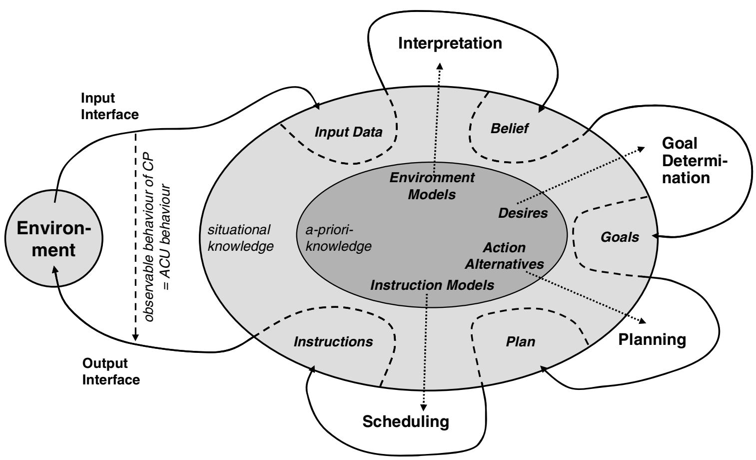

Fig. 2. The Cognitive Process

A paradigm for the design for artificial cognitive systems with such capabilities is the Cognitive Process (CP) [2, 3, 4], which is depicted in figure 2. It is a model of human information processing and describes a-priori knowledge models necessary for the implementation of especially knowledge-based behavior as well as transformation steps actually processing the knowledge.

The transformer *interpretation* uses *environment models* to gather an understanding of the current situation on the basis of *input data* from the environment. This *belief* is the most important input for the *determination* of currently relevant *goals* to be achieved next. These are derived from *desires*, which describe all goals that can potentially be prosecuted by the ACU. The transformer *planning* assembles available *action alternatives* to a *plan*, which is suited to achieve the goals. Finally, the plan is being executed and *instructions* are sent to the output interface.

For the realization of ACUs based on this paradigm, the cognitive system architecture COSA [2] has been developed which provides a framework implementing application-independent parts of the CP, i.e. knowledge processing by the transformers. Moreover, the development of application-specific a-priori knowledge is supported by the Cognitive Programming Language CPL, which allows to actually formulate environment models, desires, action alternatives and instruction models.

3 Co-operative UAV Guidance

Based on this approach to design and implementation of artificial cognitive units capable of knowledge-based behavior, a mission management system for UAVs has been developed, which is capable of co-operative mission accomplishment in a manned-unmanned team. In concrete terms, a team consisting of a manned aircraft and several UAVs each of which is guided by such an ACU receives a mission order from an operator and has to co-ordinate itself in order to successfully accomplish the mission. This section at first details the full range of capabilities the UAVs have to cover before our approach to realize co-operative behavior and its modeling and implementation on basis of the Cognitive Process and COSA are being described.

3.1 Required Capabilities

According to [5], several capabilities have to be covered by a UAV guidance system in order to be able to successfully accomplish co-operative missions such as the one sketched in figure 1. These are:

- *System management*, i.e. controlling flight guidance systems such as an autopilot
- *Safe flight*, i.e. ensuring collision avoidance with e.g. other aircraft or terrain
- *Single vehicle mission accomplishment*, i.e. the ability to actually accomplish certain mission relevant tasks, which have been assigned to a UAV
- *Co-operative mission accomplishment*, i.e. the ability to achieve the common mission objective together with other assets which includes co-operation, co-ordination and communication (see section 3.2)

The scope of the work presented within this paper was mainly co-operative mission accomplishment on the knowledge-based level of performance while the other capabilities were just considered as much as necessary for co-operation.

3.2 Co-operation

Within a human-ACU team, the ACUs involved have to co-operate with both human team members and other ACUs. Co-operation means that several agents, i.e. humans and/or ACUs, work together, in order to achieve a common objective (cf. e.g. [6]). Different tasks assigned to the team members involved contribute to this common objective. Usually, these tasks are not independent from each other (cf. e.g. [7]). For example, one task has to be completed before another one can be started or several team members need a common resource. Such interdependencies have to be resolved in order to ensure efficient teamwork. Therefore, the framework of commitments, conventions and social conventions described by Jennings [8] is being used, which allows reasoning on working together on a high level of abstraction. An important means for co-ordination is communication, i.e. the exchange of information among agents. For communication of the ACUs the Agent Communication Language specified by the Foundation of Intelligent Physical Agents (FIPA, www.fipa.org) is being used. It provides the description of a message format, performatives and content languages, as well as interaction protocols. The latter define what kind of messages have to be exchanged in order to achieve a certain objective. For example a ‘request interaction’ can be used to ask another team member to complete a certain task.

3.3 Modeling and Implementation

In order to provide ACUs with the capabilities described in sections 3.1 and 3.2 appropriate knowledge has to be modeled, i.e. desires, action alternatives, instruction models and environment models of the a-priori knowledge of the Cognitive Process (see section 2) have to be identified.

As co-operative behavior shall be exhibited on the knowledge-based performance level, above all appropriate desires have to be identified to implement co-operative capabilities [9]. These refer to the achievement of the common objective by committing and dropping commitments to tasks appropriately and actually completing assigned tasks. Secondly, working together as a team is being addressed by appropriate information exchange, distribution of tasks among team members and setting up a team structure. Thirdly, the co-ordination of interdependencies among the activities of agents is taken into account and finally, a desire producing communication within the team is being modeled. Action alternatives mainly refer to the initiation of dialogs and communicative acts, i.e. sending messages. An instruction model describes the message protocol used. Finally, a comprehensive understanding of the current situation is necessary for knowledge-based behavior. This is gathered by the implementation of environment models comprising concepts such as actor, team, resource, task, dialog and commitment.

The interaction of several models of the implemented a-priori knowledge shall be explained taking the distribution of workload within an ACU team as example. Figure 3 shows several models of the a-priori knowledge of the developed ACU (continuous frame) as well as instances of these models (dotted frame). Here, two actors (*actor-self* and *actor-1*) as instances of the environment model **actor** exist within the situational knowledge of the considered ACU which is associated with *actor-self*. Moreover, there are two instances of **task-destroy** (*task-destroy-0* and *task-destroy-1*). While *actor-1* is committed to both tasks (two instances of **commitment**), there is no commitment of *actor-self* to any task. This results in the conclusion, that workload of actor-self is low (cf. attribute *is* of instance *workload-0* of **workload**) while the workload of actor-1 is high (cf. attribute *is* of instance *workload-1* of **workload**). So far, the current situation has been interpreted, i.e. instances of environment models have been created and their attributes have been assigned values.

Activation criteria of the desire **balance-workload** comprise the knowledge, that **balance-workload** shall be pursued as active goal in case the workload of one actor is low while the workload of another actor is high. As this is the case, an instance of **balance-workload** is created within the situational knowledge. To achieve this goal, several actions are possible from the perspective of *actor-self*, namely to propose to take over *task-destroy-0* or to propose to take over *task-destroy-1*. Both are instances of the action alternative **propose**. As there are more than one possible ways to achieve

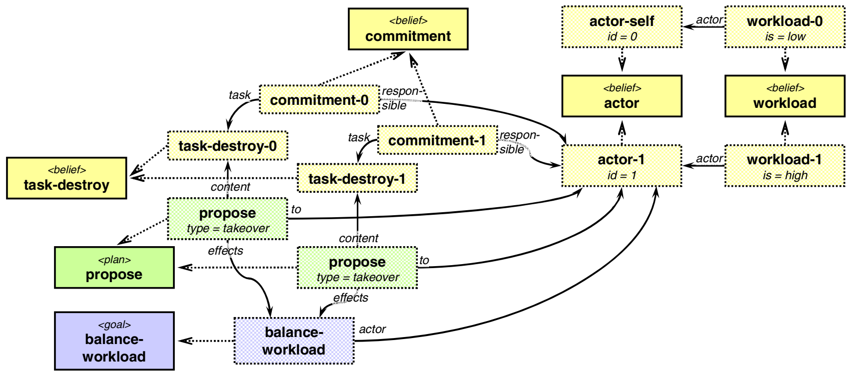

Fig. 3. Interplay of models (a-priori knowledge) and instances (situational knowledge) [9]

the active goal, appropriate selection knowledge has to be used to choose from the action alternatives being available. Assuming, that *actor-self* selects to propose taking over *task-destroy-0* from *actor-1*, an appropriate dialog will be initiated and conducted, again leading to the instantiation of a-priori knowledge models including the activation of desires.

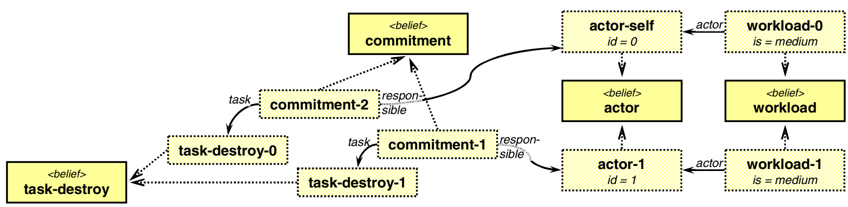

Fig. 4. Models and instances thereof after appropriate actions have been successfully carried out in order to achieve goal "balance workload"

This interaction results in a change in commitments, which is also communicated to other team members and reflected within the situational knowledge (cf. figure 4). In concrete terms, there is no commitment of *actor-1* to *task-destroy-0* any more (previously *commitment-0*), but instead, *actor-self* has committed to *task-destroy-0* (*commitment-2*) and the workload of both actors is assumed to be "medium" now. Thus, the desired situation has been reached and there is no reason for an ongoing activation of the desire "balance-workload" any more.

This example is based on assumptions about the workload of the team members involved. While for machine team members, workload can quite easily be inferred from task load, for human team members, more elaborate models have to be introduced here.

In this way, appropriate knowledge has been implemented referring to all desires relevant to co-operative capabilities mentioned above (see [9]). Moreover, application specific capabilities have been considered which are necessary for the evaluation of the developed prototype that will be described in the next section.

4 Evaluation

The evaluation of the ACUs capable of co-operatively accomplishing a multi-UAV mission was conducted using a simplified air-to-ground-attack mission as an example (cf. figure 1). The ACUs were evaluated from three perspectives, namely (1) achievement of the specified functionality in a pure ACU team, (2) capability to behave on knowledge-based performance level, and (3) co-operation within human-ACU team. As there are detailed reports on the achievements regarding item (1) (e.g. [9, 10]), this paper will focus on knowledge-based behavior and human-ACU co-operation.

4.1 Knowledge-Based Behavior

Section 2 gave an overview of the characteristics of knowledge-based behavior, which most notably comprises the orientation of behavior towards explicit goals in situations for which no direct situation-task mapping is available. For the purpose of clarity, knowledge-based performance shall here be illustrated using a single vehicle sub-problem as example.

Figure 5 top left shows a UAV on its flight back to the home base. It is currently within the range of a temporarily shutdown SAM site, which can re-activate at any point in time. Relevant goals of the ACU guiding the UAV within this context are the avoidance of (potential) threat by the SAM site as well as flight to the home base. The action alternatives it has at hand are to fly away from the SAM site or to plan and

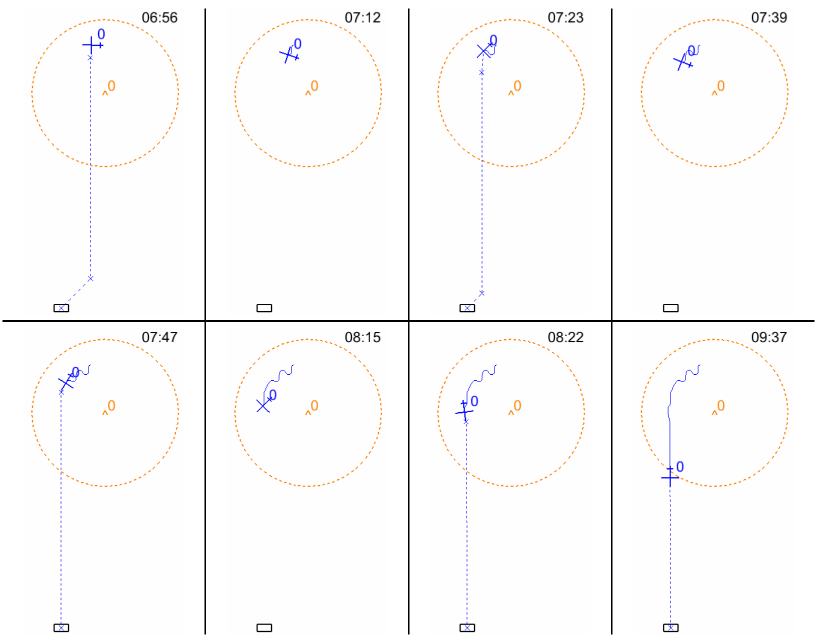

Fig. 5. Knowledge-based balancing of threat exposure and route following [9]

activate a flight plan which can not consider potential threat. Therefore, no action alterative is suited to achieve both goals at the same time.

Still, in the end the UAV flies a trajectory which in principle satisfies both goals mentioned above (see figure 5 bottom right). This trajectory results from a situation-adapted prioritization of active goals and selection of action alternatives. Based on an interpretation of the current situation, the ACU decides at some points in time that it is more important to escape the potential threat of the SAM site and chooses the appropriate action alternative (see figure 5, 7:12, 7:39, 8:15), while in other situations the goal to fly to the home base which is achievable by planning and activation of a route is being pursued (see figure 5, 6:56, 7:23, 7:47, 8:22, 9:37).

Of course, the resulting trajectory is not as optimal as it could have been when using a highly specialized algorithm for trajectory generation. But although there was no such expert knowledge or capability within the system, behavior could be observed, which does follow explicitly represented super ordinate goals and which is close to expected behavior. [9]

4.2 Human-ACU Co-operation

In order to gain insight to problems arising in human-ACU co-operation and derive requirements for future ACU development, an experiment has been conducted, where human pilots had to control up to three UAVs equipped with ACUs to accomplish a mission as described in figure 1 [9, 11]. It was expected, that humans would be able to manage the guidance of one UAV but workload would exceed an acceptable level when increasing the number of UAVs.

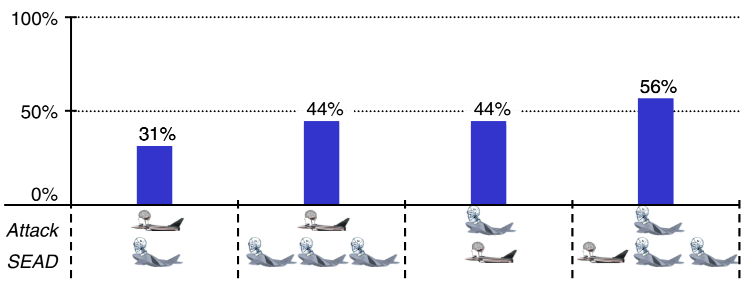

Fig. 6. Average workload of subjects in different configurations

To investigate this, five experienced military air crew members were asked to work together with one or three UAVs in different roles (attack or SEAD, cf. figure 6, bottom) and scenarios. The manned aircraft could be controlled on autopilot level. Co-operation within the human-ACU team was based on the exchange of information on capabilities, resources, i.e. weapons, and commitments via a graphical user interface. Moreover, task requests could be sent to either individual UAVs or the whole UAV team. After each run workload was measured using the NASA-TLX method [12] and the subjects were interviewed.

Figure 6 shows the average workload of subjects against the configuration. Interestingly, workload is on a medium level in all configurations that have been investigated and there is only a small increase in workload when changing the number of UAVs within the team from one to three. Moreover, the increase in workload when changing the human role from attack to SEAD is as large as when adding two UAVs, which could be related to different performance of UAVs in the SEAD and attack role.

These results show that human-ACU co-operation works well with the approach of cognitive and co-operative automation. Still, further improvement potential was identified in the following areas after having analyzed interview protocols:

- *Team Structure.* The introduction of a hierarchical team structure is encouraged, although team members shall be capable of situation dependent deviation from leader input.
- *Abstraction of Interaction.* Interaction with ACUs shall be as abstract as possible (e.g. specification of tasks for UAV team rather than detailed instructions for single UAVs). In particular it shall be possible to give instructions on different abstraction levels.
- *Level of Automation.* ACUs shall be able to act on a high level of automation but the actual level shall be adaptable or self-adapted to the current situation and task.
- *Teamwork.* Co-operation of humans and ACUs shall be based on a common agenda and anticipate future actions of team members.
- *Task completion.* The capability of ACUs to actually accomplish tasks has to be improved.
- *Communication within team.* Vocabulary shall be adapted for more intuitive understanding of humans. Moreover, the number of dialogs and messages shall be reduced to a minimum in order to avoid overload of humans.
- *Assistant System.* The human team member shall be supported by an electronic assistant providing situation awareness concerning team members, task assignment and information flow within team as well as accomplishment of the primary mission related task, i.e. aircraft guidance.

5 Summary

While humans are capable of goal-directed behaviour even in situations they have not experienced before, conventional automation systems usually lack the capability to understand the situation, identify relevant goals and plan actions which can transform the current situation into the desired one. Cognitive automation in contrast is capable of such knowledge-based performance and can therefore be used to develop Artificial Cognitive Units as advanced UAV guidance systems for usage in highly complex and unpredictable scenarios. The Cognitive Process has been used as paradigm for the design of co-operative Artificial Cognitive Units and applied to co-operative UAV guidance. The concept and some implementation details of co-operative capabilities have been described before the resulting capabilities of the ACUs have been discussed. Hereby, at first the capability of the developed ACUs to behave on the knowledge-based level of performance has been explained and the importance of explicitly represented goals within the situational context has been reported on. Finally, the promising results of a human-ACU teaming experiment have been presented, where a human operator could work together with up to three UAVs very well. Future steps include the

application of these results in more realistic scenarios and the helicopter domain as well as field tests of ACUs using our UAV demonstrators [13]. Moreover, techniques concerning knowledge acquisition and modelling will be investigated in order to approach a system engineering process for development of cognitive automation.

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