Perception-Oriented Cooperation for Multiple UAVs in a Perception Management Framework

System Concept and First Results

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Abstract — **This article presents a concept for Multi-UAV cooperation in manned-unmanned teaming (MUM-T) helicopter missions, embedded in military search & rescue operations. Due to their highly-dynamic nature, these kinds of missions are especially challenging. Thus, it is necessary for the UAVs to perform complex reconnaissance tasks in a semiautonomous manner. As these tasks are per se driven by their perceptive demands, the UAV automation should incorporate the specific constraints and limitations of its mission sensor & perception suite when conducting such missions. The perception-oriented cooperation of multiple UAVs offers a promising way to overcome these limitations, allowing to benefit from heterogeneous payload setups as well as from varying platform characteristics. In this paper, we present the concept and prototype of the *Perception-Oriented Cooperation Agent (POCA)*, offering capabilities for the perceptive cooperation of multiple UAVs conducting complex reconnaissance missions. An integrated Multi-UAV *perception planning & scheduling* agent is described, specifically taking into account the informative needs of the H/C crew in control and the requirements of the mission sensor suite. The prototype of the planner is tested in three reduced toy problem setups, demonstrating it's Multi-UAV scheduling capabilities in different payload configurations.**

Keywords—Multi-UAV; sensor management; resource management; sensor scheduling; task planning; task based guidance; task scheduling;

I. Introduction

In today's unmanned aerial systems (UAS) still multiple ground-operators are necessary to operate a single unmanned aerial vehicle (UAV). Typically, one operator is responsible for flight guidance & platform control, while a second person handles sensor deployment & assessment. Besides the great demand on well-trained personnel and thus high operating costs, this multiple-operator-single-platform constellation induces specific problems in command & control of the UAS due to information loss and communication gaps between the operators/pilots up to platform losses and mishaps [1], effectively limiting the usage of UAS. Hence, current development aims at a reduction of the operator-UAV ratio, finally resulting in a ratio-inversion with a single operator controlling multiple UAVs at once. Obviously, this development will lead to reduced operator-costs, but will also cause new challenges in command & control, especially in terms of operator workload.

In this scope, the Institute of Flight Systems (IFS) at the University Bundeswehr Munich (UBM) investigates on the teaming and cooperation of manned forces with UAVs to accomplish complex missions and scenarios. Within this *manned-unmanned-teaming (MUM-T)* domain [2], the R&D project CASIMUS (*Cognitive Automated Sensor Integrated Unmanned Mission System*) aims at time-critical missions in highly-dynamic and unsafe environments, e.g. CASEVAC or CSAR. There, the UAVs must provide a manned helicopter (H/C) with up-to-date recce and surveillance data of potential H/C flight paths as well as of potential landing and drop zones. Furthermore, the UAVs should be guided from on board the H/C to reduce command & control (C2) latencies and increase operational flexibility [3]. Thus, command & control of the UAVs as well as sensor deployment and data assessment needs to be integrated into the task spectrum of the helicopter crew to achieve higher *levels of interoperability* (LOI 4/5, [3]) giving the crew faster and more flexible access to recce data. However, moving the C2-loop from a dedicated ground control station to the cockpit bears the risk to greatly increase the workload of the mission commander, which must be handled in an appropriate way [4], [5]. Therefore, guiding UAVs at LOI 4/5 requires them to be highly automated, both in terms of mission management and sensor deployment automation.

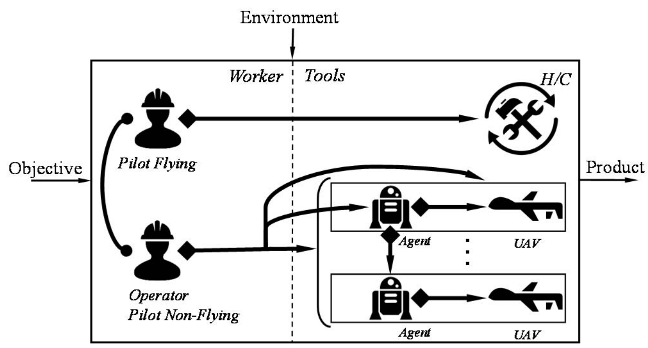

Fig. 1. Automation scheme for H/C-based multi-uav control expressed as a work system by Onken and Schulte [4], [6].

Fig. 1 depicts the general scheme for such automation systems, in which a single operator, here the pilot non-flying, controls UAVs through the support of artificial agents on-board the unmanned vehicles, allowing for human-machine interaction with varying levels of automation (LOA) [7].

To be embedded in this scheme, this article describes *POCA (Perception-Oriented Cooperation Agent)* as an example concept for such on-board agent system. Its goal is to support the crew in the accomplishment of complex perception-driven tasks like *Landing Zone Reconnaissance (LZR)* in a semi-autonomous manner, focusing on the related sensor and perception planning aspects.

The paper is structured as follows: Section II compares previous and related work, influencing the concept design. Thus, the overall system concept is presented in section III, stating conceptual requirements and drafts the system. First implementation aspects are pointed out in section IV, accompanied by a description of the system architecture. Section V presents some preliminary experiments with their results. Finally, section VI concludes this article and gives an outlook on further research.

II. Foundations

In order to achieve semi-autonomous execution of complex mission related tasks by unmanned vehicles, several high-level automation paradigms were investigated. In [8], Uhrmann and Schulte proposed the concept of *Task-Based Guidance* explicitly utilizing the paradigm of *Cognitive Automation* [10]. The concept implies that a UAV must be able to deduce its own course of actions in order to fulfill operator-given mission tasks incorporating mission-related constraints, actual situational circumstances and background knowledge. The general idea is to provide automation mechanisms when needed to reduce the operator's mental workload, allowing to shift his mental resources from raw UAV platform control to higher, more mission-related tasks, especially in multi-UAV scenarios [10], [11]. Although the approach shows remarkable results, experimentation so far focused strongly on UAV guidance while tasks related to handling the mission sensor & perception suite were greatly simplified in a way similar to Miller's *Playbook* [12], leading to a demand for a high-level automation paradigm to cope with sensory and perceptual issues.

Russ and Stuetz first proposed a concept for *Sensor & Perception Management* (SPM) in [13] for single-UAV operations, addressing the need to automate on-board perceptual capabilities and thereby linking the ideas of sensor management [14], [15] and task based guidance. The paradigm suggests the idea of the *Perception Graph* to model the processing interdependencies between mission sensors and applicable computer vision modules, semantically expressed as discrete *Perception Tasks* which are known and understood by a superordinated *Mission Management System* (MMS). This allows the MMS to integrate the perceptive subtask in its own agenda created on the base of high-level mission tasks intended by the UAS operator [16]–[18]. The goal is to hide the complex processing internals of the perception resources, e.g. domain and environmental constraints and optimizations, only providing information's necessary to activate desired perceptual capabilities.

Fig. 2 depicts this interaction between the MMS and the *Sensor & Perception Management System* (SPMS). Here, the MMS knows the mission objective and decomposes it in navigational and perceptive sub-tasks which are delegated to the respective subsystems, i.e. the FMS and the SPMS. The SPMS is then selecting the appropriate mission sensors and perception modules, e.g. suitable computer vision algorithm, to fulfil the requested perception task based on actual environmental conditions and the UAV flight state [19], [20].

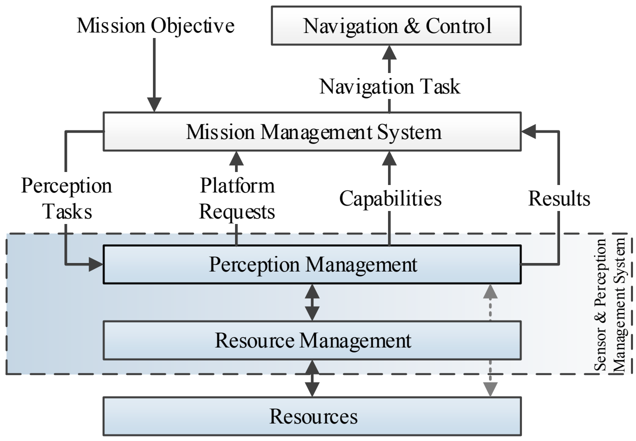

Fig. 2. Sensor & Perception Management Paradigm [13], [21].

Hellert and Smirnov further elaborated this approach in [21], incorporating aspects of the *Active Perception* paradigm as proposed by Bajcsy in 1988 [22] to dynamically adopt the system to available resources and capabilities, i.e. available mission sensors or processing resources. Their concept also incorporates the usage of perception modules with different levels of granularity requiring a detailed description of the modules capabilities and constraints [23] explicitly modelled in an OWL-based [24] *Perception Resource and Capability Ontology,* commonly used throughout the presented framework [25]. *Description Logic* (DL) reasoning is applied whenever a system state changes, allowing it to adapt on changing circumstances, e.g. a malfunctioning sensor.

OWL-based ontologies are also used by Bouillet et al. [26] to model sensory and perceptual resources for the design and formulation of stream processing planning problems. In their approach, a plan, consisting of states, goals, and actions, is represented as an RDF graph [27], [28] and its respective transformations, allowing a DL reasoner to check the applicability of a plan action for a state to achieve a specific goal which is then used by a SPPL-based planner [29] to decompose the actions and create the processing workflow.

III. Concept

An example for a CASEVAC mission is depicted in Fig. 3. Here, an unarmed transport-helicopter shall rescue a group of crashed journalists in a highly dynamic and unsafe environment, typical in today's asymmetric conflicts. In the example, the crash site of the journalist's H/C is known, determining the landing zone for the rescue mission. Therefore, a safe landing point shall be detected by the UAVs, making it necessary to gather numerous and heterogeneous data from (multiple) potential landing points and rate them with respect to suitability. For that, a sequence of interleaved perceptive and navigational tasks shall be performed by the UAVs, incorporating the specific requirements of the perceptive subtasks and constraints resulting from the tactical situation, whereby the different constraints could be conflicting.

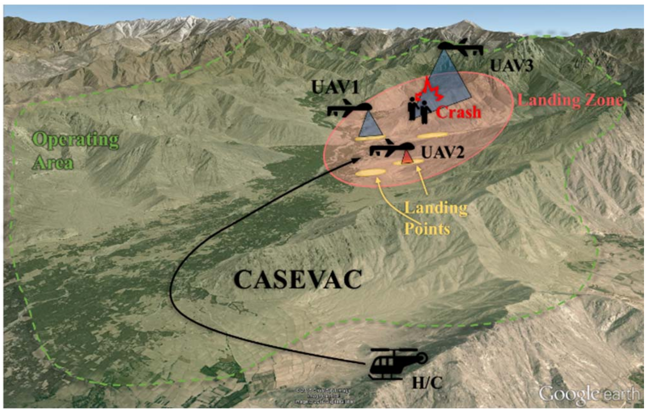

Fig. 3. Example for Landing Zone Reconnaissance in a CASEVAC scenario: The transport helicopter conducting CASEVAC aims in rescuing a pair of crashed journalists in an unsafe environment, supported by a team of 3 heterogenously-equipped UAVs searching for suitable landing points (light yellow) in the designated landing zone (light red).

While the SPM systems in [13], [21] provide highly reactive solutions for the execution of perceptive tasks, incorporating sophisticated mechanisms for environmental self-adaption, the concept is restricted so far on single UAV operations aiming at single recce targets. Thus, it lacks features necessary to accomplish complex perceptive sequences in a UAV team as needed for the *Landing Zone Reconnaissance* task above:

- The ability to deliberatively create a course of action for the information gathering process, i.e. to create sensor- & perception-optimized plans.
- The ability to combine multiple UAVs, benefitting from heterogeneous sensor and perception suites as well as the possibility to speed up information gathering.

In order to cope with the shortcomings mentioned, we would devise an on-top agent system for *Perception-Oriented Cooperation*, extending the concepts presented in [13], [21].

Fig. 4 illustrates the basic principle of operation. A perception task is assigned to the system along with external constraints and available system resources. The agent system analyzes the task along with provided information to initialize task planning, taking into account the perceptual capabilities and limits of the underlying SPM systems as well as their operational requirements extracted from the *Perception Capability Ontology* [25], merged into a holistic team capability model of the cooperating UAVs, additionally incorporating knowledge about applicable sensor fusion and cooperation techniques. Furthermore, explicitly modelled *Information Needs* are determining the planning goals. Combining these, a task agenda is created, consisting of interleaved navigational and sensor deployment tasks which are subsequently used to control the single UAV automation systems, i.e. the SPMS and the FMS. During execution, the outcome of the perception tasks is monitored and the plan is adapted and refined as needed. Finally, a fusioning system combines the perceptive results of the UAVs.

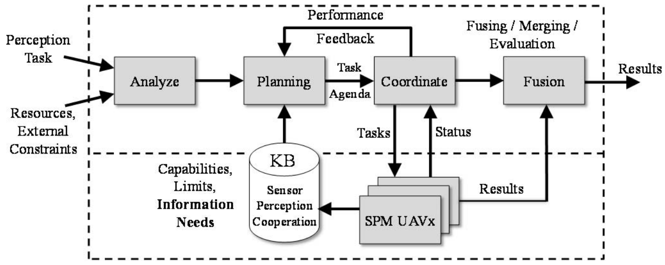

Fig. 4. Operational principle for perception-oriented cooperation.

IV. Implementation Aspects

A module decomposition along the functional principle explained before is illustrated in Fig. 5, presenting the overall system architecture for the Perception-Oriented Cooperation Agent (POCA), building on the architectures presented in [13], [21]. Consequently, it is designed as a hierarchical multi agent system, consisting of a mix of a knowledge-based agent systems, including the single-UAV SPMS mentioned before (cf. Fig. 2), and traditionally automated subcomponents, such as sensor control, gimbal automation, and computer vision algorithms.

Three key extensions were identified which need to be addressed separately in order to design POCA: A. *information demand determination*, B. *ontology combination*, and C. *perception-oriented planning & scheduling*.

A. Information Demand Determination

First the planning goal has to be determined. In our system, it is defined by the information needed by a superordinated level, e.g. the MMS or the human operator, for a given recce target. Thus, it inherently defines a set of perceptive tasks and recce actions to be performed by the UAVs where each single tasks could have sequential requirements due to tactical or technical considerations. For example, the UAVs should check for hostile forces prior to obstacle scanning (cf. Fig. 6).

These interconnections are modelled explicitly in the *Information Demand Model* (IDM). In the *Landing Zone Reconnaissance* use case, the IDM defines the H/C crew's requirements on landing zones and the respective landing points, both from a tactical and an operational point of view, e.g. enemy clearance or the size of a landing point.

A deeper insight of the model is provided in [30].

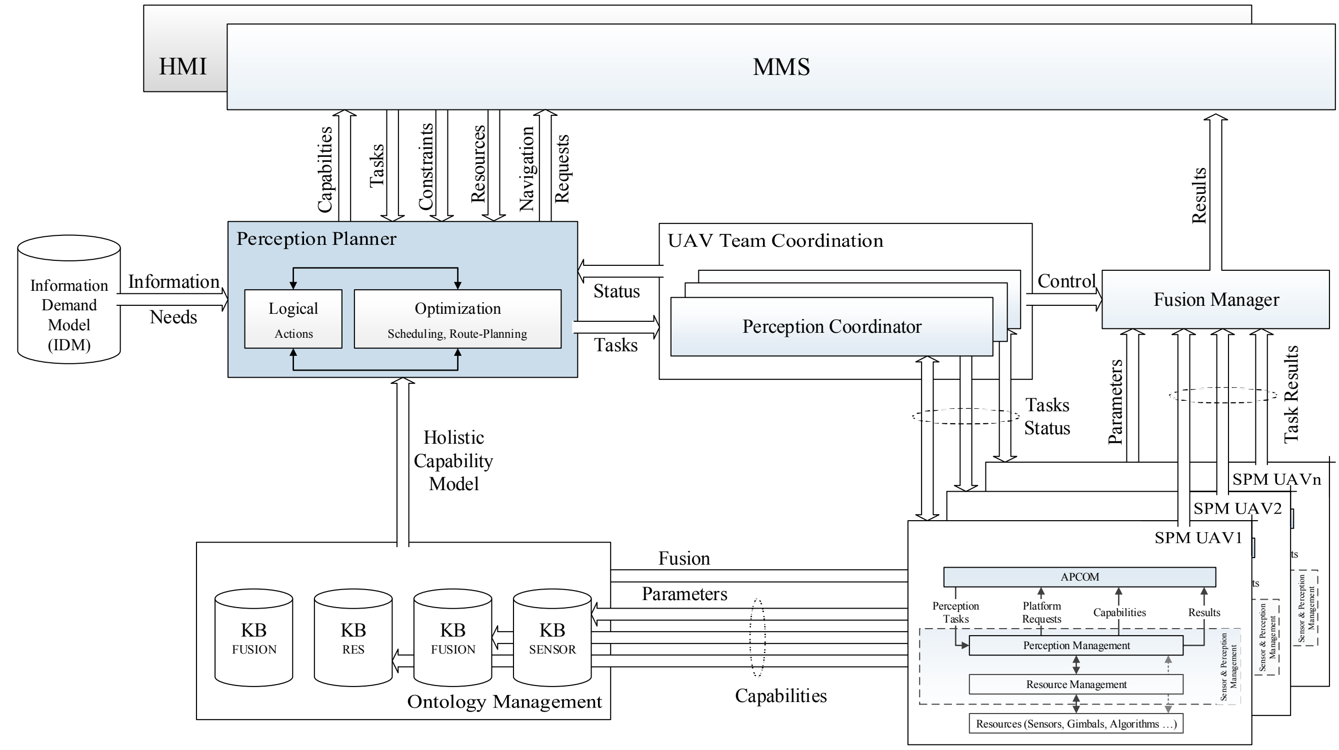

Fig. 5. Overall system architecture of the Perception-Oriented Cooperation Agent (POCA).

B. Ontology Combination

Secondly, the cooperation model proposed in this paper is based on capability-based cooperation. Therefore, *POCA* relies on a model of available capabilities with respect to given resources. To obtain a model of a single UAVs sensor and perception capabilities, the merging agent shall build on knowledge already inferred and semantically described by the SPMS, i.e. the aforementioned *Perception Capability Ontology* of [25].

Thereby, available resources are indirectly defined through the composition of the UAV team, whereas the team compilation process is done prior to task assignment, either by the MMS or the human operator.

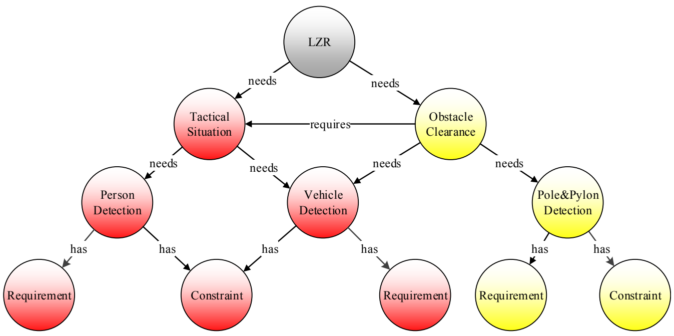

Fig. 6. An excerpt of the Information Demand Model for H/C Landing Zone Reconnaissance [30].

Thus, we propose the usage of a holistic *team capability ontology*, containing both perceptive and navigational capabilities of the UAV team members as well as additional capabilities arising from the opportunity to cooperate, namely:

- Compensation of capability gaps resulting either from heterogeneous sensor or processing suites on-board the UAVs or from different platform characteristics. For example, one UAV could be equipped with a LIDAR sensor thus providing a *3D-mapping capability* while another is only equipped with an EO-camera, therefore providing *daylight object detection capabilities*. Teaming both UAVs, the team has both types of capabilities (cf. Fig. 7).

- Formation of new capabilities, only possible due to cooperation or coordination mechanisms. Continuing with the previous example, two of the above mentioned EO-camera UAVs could substitute the 3D-mapping capability by using a *cooperative stereo vision capability*, i.e. use the camera views from two UAVs flying in parallel to generate a 3D image.

- Satisfaction of tighter time constraints through parallelization & serialization of task execution, e.g. in the LZR domain, a team of UAVs could check multiple landing points quicker than a single one.

These capabilities are mapped to UAVs either in $1:1$ or $1:n$ relations, allowing the planning agent described next to incorporate and allocate them appropriately.

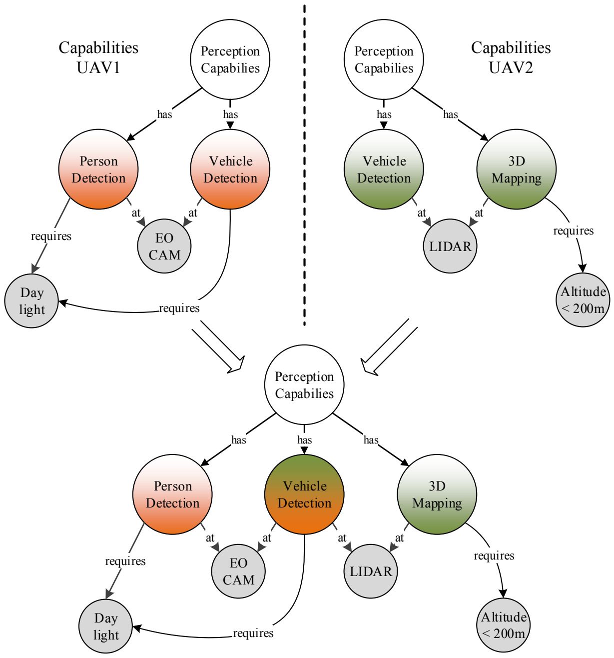

Fig. 7. Excerpt of the team capability ontology. The capabilities of UAV1 & UAV2 are merged to create the team capability model.

C. *Perception-Oriented Planning & Scheduling*

As final step, *POCA* must plan & schedule the actions of the team members to satisfy the specified *Information Demand*. Therefore, it extracts the available capabilities from the aforementioned capability model and matches them to the planning goals, taking into account externally defined constraints, such as airspace constraints or temporal deadlines, i.e. conditions which are neither controllable nor influenceable by the system. The Perception Planner (cf. Fig. 5) combines these to create the *Perception Task Agenda* (PTA), a set of interleaved navigational & sensor deployment tasks which should be executed accordingly by the UAV team in a coordinated manner.

Fig. 8 shows a simplified PTA for a team of three UAVs, conduction Landing Zone Reconnaissance (cf. Fig. 3) on a landing zone containing the landing points LPA and LPB. There, UAV1 and UAV2 start at LPA while UAV3 starts at LPB. UAV2, equipped with a Direct-3D-imaging sensor (e.g. a LIDAR), must wait for UAV1 to finish tactical recce prior starting terrain recce for tactical reasons. Meanwhile, UAV3 has searched for hostile forces on LPB and goes in hold / wait position, waiting for UAV1. UAV1 flies to LPB to accomplish terrain recce in close cooperation with UAV3, allowing the team to stick to the given deadline which would be violated if terrain recce would be only executed by UAV2. After finishing the tasks, the team goes in hold position, waiting for further orders.

However, the example above describes the optimal case in which no hostile forces are detected, allowing the plan to be executed as initially planned. In a real-world scenario, the PTA has to be constantly updated depending on the world observation following a dynamic planning scheme to react on changing circumstances, e.g. to redirect UAV2 to LPB if hostile forces were detected on LPA by UAV1, marking LPA as unsafe. Therefore, the planner constantly monitors the current world state and compares it to its internally estimated state. If conflicts are detected, a replanning under the changed circumstances is executed and the PTA is updated accordingly.

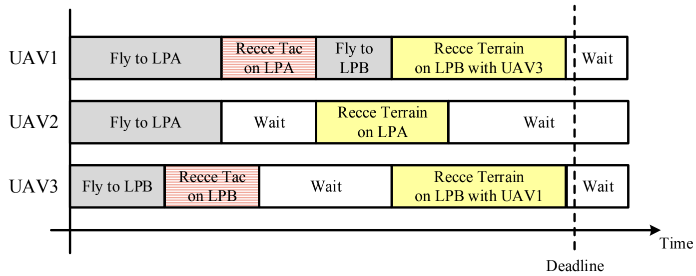

Fig. 8. Temporal view of a simplified Perception Task Agenda for a team of three UAVs conducting Landing Zone Reconnaissance. Cyan boxes mark navigational tasks, red and yellow boxes are perceptive tasks.

In this case, the Direct-3D-capability of UAV2 could be used to execute terrain recce on LPB. Additionally, this allows the planner to cope with uncertainties in the recce results, thus increasing the reliability of the perceptive outcome [5], [20], if there is enough time left. For example, it could insert additional flyovers to gather further data or rescan specific areas.

Also, the investigated highly dynamic missions require the planner to have rapid replanning and scheduling capabilities, allowing the system to encounter fast situational changes as the detection of enemy forces mentioned above, resulting in a requirement for the planning time of about 1 to 3 seconds and a real time requirement on the monitoring and update process. As a consequence, the perception planner is designed as a two-tier architecture (cf. Fig. 5), consisting of a *logical* planner, determining the perceptive and navigational actions, and an *optimization* component, scheduling and assigning the determined actions to the available resources. In addition, the optimizer is divided in a CPLEX-based [31] constraint optimizer and a subordinated route planner for performance reasons. An additional separation layer was used here to allow the integration of sophisticated route planning libraries [32] while simultaneously maintaining a reasonable search space for the constraint optimizer. Fig. 9 depicts planning architecture in more detail and visualizes this plan-generation process.

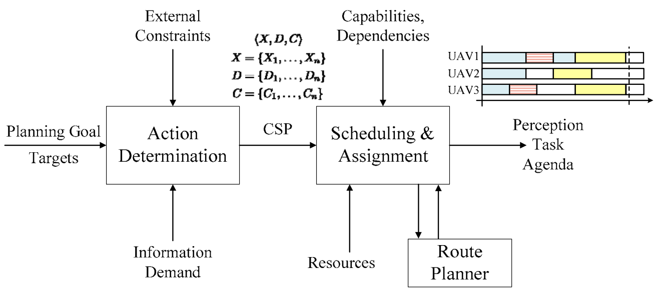

Fig. 9. Architecture of the Perception Planner, consisting of an logical component (Action Determination) and an optimization component (Scheduling & Assignment and Route Planner).

The logical planner determines the perceptive and navigational actions for the planning goal, e.g. "recce landing zone A". Therefore, it combines *Information Needs*, designated recce targets and external spatiotemporal constraints, to formulate a constraint optimization problem (COP) [33] for the adjacent task scheduling and assignment process. Thereby, the CSP is defined as the tuple

$$\langle X, D, C \rangle \tag{1}$$

with

- $X = \{X_1, \ldots, X_n\}$ denoting the variables, i.e. the tasks to be scheduled on the recce targets,
- $D = \{D_1, \ldots, D_n\}$ denoting the domain for each variable X_i, representing its possible states, e.g. target clearance state, and
- $C = \{C_1, \ldots, C_n\}$ denoting a set of constraints to fulfill for all variables X, i.e. no-fly-zones or temporal deadlines.

Thus, the CPLEX-based constraint optimizer solves the CSP (1), minimizing plan execution time and maximizing information gain. Therefore, it utilizes available capabilities of the UAVs, additionally incorporating their specific dependencies into the CSP, e.g. maximum velocity or required time-over-target. Furthermore, the subordinated route planning module is used during optimization & plan refinement to estimate flying times of the UAVs.

V. Preliminary Results

To proof the concept of perception-oriented planning and thus to test the first prototype of POCA, a toy setup of the aforementioned *Landing Zone Reconnaissance* was designed as a real-world evaluation example. Fig. 10 shows the tactical situation for the toy problem, embedded in a bigger CSAR mission. There, a group of journalists had crashed in unsecured territory who must be rescued (cf. the use case described in section III).

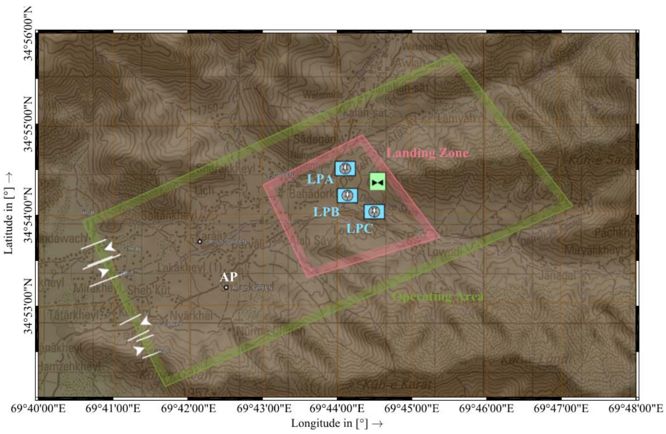

Fig. 10. Toy setup for *Landing Zone Reconnaissance* in a CSAR scenario. The landing zone (pink) contains 3 landing points (blue) to be cleared.

Using a geographic information system, three potential landing points LPA, LPB and LPC were selected based on the geographic and technical requirements of the rescue H/C, e.g. minimal size of a landing point or the maximum tolerable slope due to mast moment restrictions [30]. To minimize the rescuing helicopter's endangerment when landing, now a team of UAVs must recce the landing points beforehand in order to select the most secure and suitable landing point. For this, POCA creates a PTA to coordinate the UAVs in the landing zone, minimizing their time-on-target and thus their risk of discovery.

In our test setup, the UAVs must perform four perceptive tasks on each landing point: person detection (PD), vehicle detection (VD), obstacle detection (OD) and slope measurement (SM). Thereby, the first two are of tactical nature and thus must be completed prior obstacle detection and slope measurement could be safely executed. These constraints are a direct consequence of the corresponding recce sensor as follows:

- Electro-optical (EO) and infrared (IR) cameras providing the PD and VD capability due to high ranges and fast processing, reducing the risk of discovery for the conducting UAV.
- A 3D LIDAR sensor providing OD and SM capability, which requires the UAV to fly on lower altitudes with lower speeds to deal with higher processing times.

Thus, we can formulate the COP (1) for the toy setup with the variables $X = \{X_{LPA}, X_{LPB}, X_{LPC}\}$, whereas each $X_{LPn} = \{X_{PD}, X_{VD}, X_{OD}, X_{SM}\}$, each in the domain $D = \{D_1, D_2\}$, denoting if a target X_{LPn} is already cleared or not for the respective perceptive task X_{PTn}. Thereby, the constraints $C = \{C^L, C^P, C^S\}$. are divided in the logical presence constraints $C^L = \{C_1^L, C_2^L, C_3^L, C_4^L\}$, enforcing the execution of every task X_{PTn} on each landing point X_{LPn}, the precedence constraints $C^P = \{C_1^P, C_2^P, C_3^P, C_4^P\}$, guaranteeing the tactical considerations described before, and the sequence constraints $C^S = \{C_1^S, C_2^S\}$, restricting the UAVs to execute only one task at a time and allowing only one UAV per landing point at the same time.

Furthermore, a model of the UAV transitions between the landing points as obtained from the route planner (cf. section IV.C) is included. TABLE I. lists the respective transition distances and times. The last column denotes the transition from a landing point to itself, needed for rescanning purposes. Thereby, the UAVs have a speed en route of $v_{er} = 70\ m/s$.

TABLE I. Landing Point Transitions

Transition	Distance d_T $[m]$	Time t_T $[s]$
LPA ↔ LPB	780.0	11.1
LPA ↔ LPC	795.7	11.4
LPB ↔ LPC	1499.0	21.4
LPx ↔ LPx	250.0	3.6

In addition, processing time estimations for the conducted perceptive tasks are extracted from the capability model, limiting the recce speed for EO/IR based capabilities to $v_{EO} =$

$40\ m/s$ and to $v_L = 15\ m/s$ for the LIDAR based capabilities (cf. TABLE II.

TABLE II. PROCESSING TIME ESTIMATIONS

Capability	Time t_P [s]
Person Detection	15.0
Vehicle Detection	20.0
Obstacle Detection	45.0
Slope Measurtement	35.0

To show the advantages of perception-oriented cooperation in such scenarios and to demonstrate POCA's capability to cope with varying and heterogeneous capabilities, different UAV combinations were evaluated:

- Setup 1 (Reference): A single UAV, having an EO and IR camera as well as a LIDAR sensor, providing all capabilities for person detection, vehicle detection, obstacle detection and slope measurement;
- Setup 2: Two UAVs, both equipped with EO, IR and LIDAR sensors, with all capabilities as the single UAV in Setup 1;
- Setup 3: Three UAVs, one equipped with EO, IR and LIDAR sensors, providing all capabilities (cf. Setup 1), the two others sharing the capabilities between them: one equipped with sensors providing capabilities for only person detection and *vehicle detection (EO, IR),* the other on equipped with *a* LIDAR sensor for obstacle detection and slope measurement;

In all setups, it is assumed that the UAVs are already in the midst of the landing zone when starting *Landing Zone Reconnaissance*.

The spatial representation of the created PTAs are depicted in Fig. 11 (reference) and Fig. 12 (Setup 2 + Setup 3). There, UAV1 is colored in red, UAV2 in green and UAV3 in blue. The performed tasks are neglected in the spatial view for reasons of simplicity. A detailed view of the task sequences and their scheduling is depicted in Fig. 13, illustrating the temporal aspects. There, the tasks are colored according their category: person detection in red, vehicle detection in orange, slope measurement in yellow and obstacle detection in green. The transitions between the landing points are depicted in grey.

In the reference setup, all landing points must be cleared by UAV1. Thus, the PTA for the single UAV setup contains of a sequential list of task to be performed by UAV1, first clearing LPB, LPA and LPC from a tactical point of view (PD + VD) and then executing the topographic tasks (SM + OD). An overall time for landing zone clearance of $t_{S1} \approx 420\ s$ is needed, leaving not much room for further optimizations due to the constraints described above.

Adding a UAV2 in Setup 2 allows the perception planner to parallelize their actions. Thus, UAV1 conducts a full landing point recce at LPC, whereas UAV2 starts with tactical recce of LPA, then continuing with tactical and topographical recce of LPB whilst UAV1 finishes the landing point clearance for LPA. The perceptive capability parallelization leads to an overall recce time of $t_{S2} \approx 220\ s$ for setup 2, saving around 47 % of the recce time.

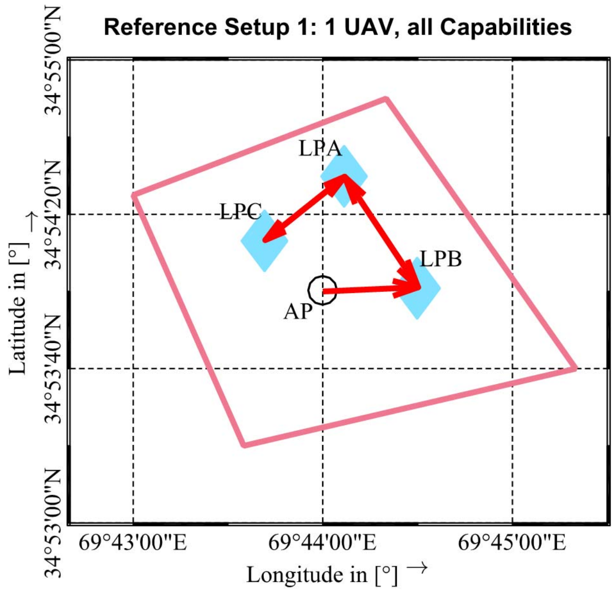

Fig. 11. Spatial visualization of the PTA for the reference Setup 1. All tasks are executed sequentially by UAV1 (red). The landing points are marked by cyan diamonds while the pink polygon marks the landing zone.

Setup 3 adds UAV3 to the planning space, allowing for further task parallelization, but restricting the capabilities of UAV1 and UAV2. Although the performance of the two restricted UAVs is not as nearly as high than of UAV3, the separated task allocation aspect allows them to cooperatively finish recce of LPA and LPB whilst UAV1 investigates LPC. Thus, setup 3 results in an overall recce time of $T_{S3} \approx 190\ s$, a reduction of about 55 % compared to setup 1 and 14 % compared to setup 2.

The results in the three exemplary setups demonstrates that perception-driven applications as the *Landing Zone Reconnaissance* scenario could benefit from perception-oriented planning and cooperation, even though the prototype of POCA presented here is still in an early stage of development. Nevertheless, further work on the planning and scheduling agent is necessary to enable additional cooperation mechanisms, for example to allow multiple UAVs work together on a single landing point. Furthermore, the optimization criteria should be reviewed in terms of information gain and information entropy minimization.

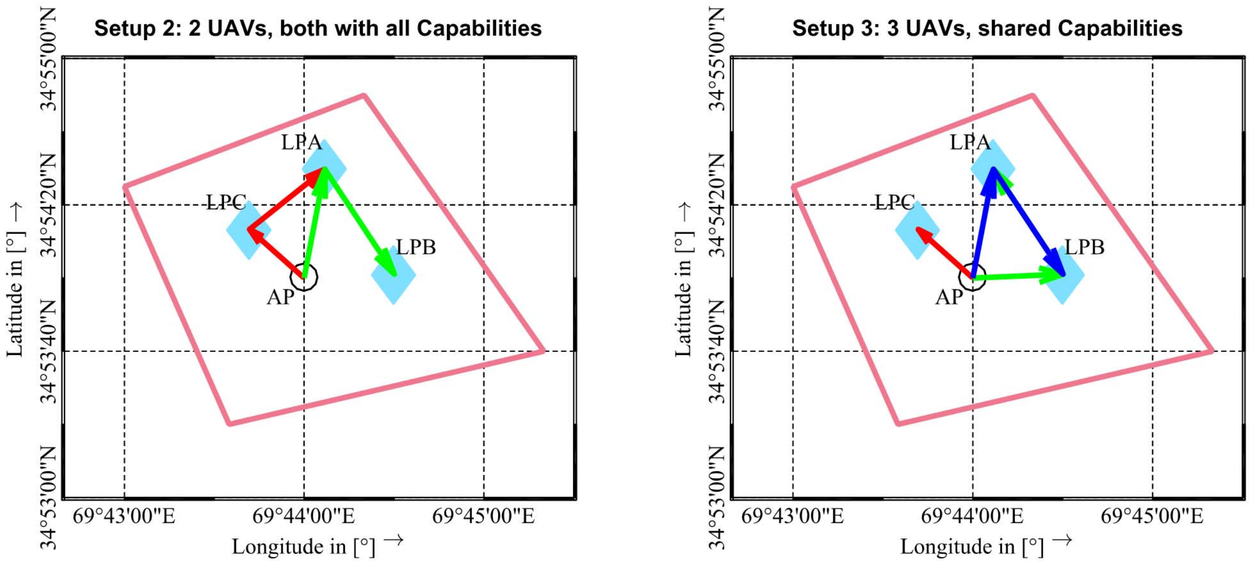

Fig. 12. Spatial visualization of the PTA for the experimental Setups 2 + 3. UAV1 is depicted in red, UAV2 in green, and UAV3 in blue.

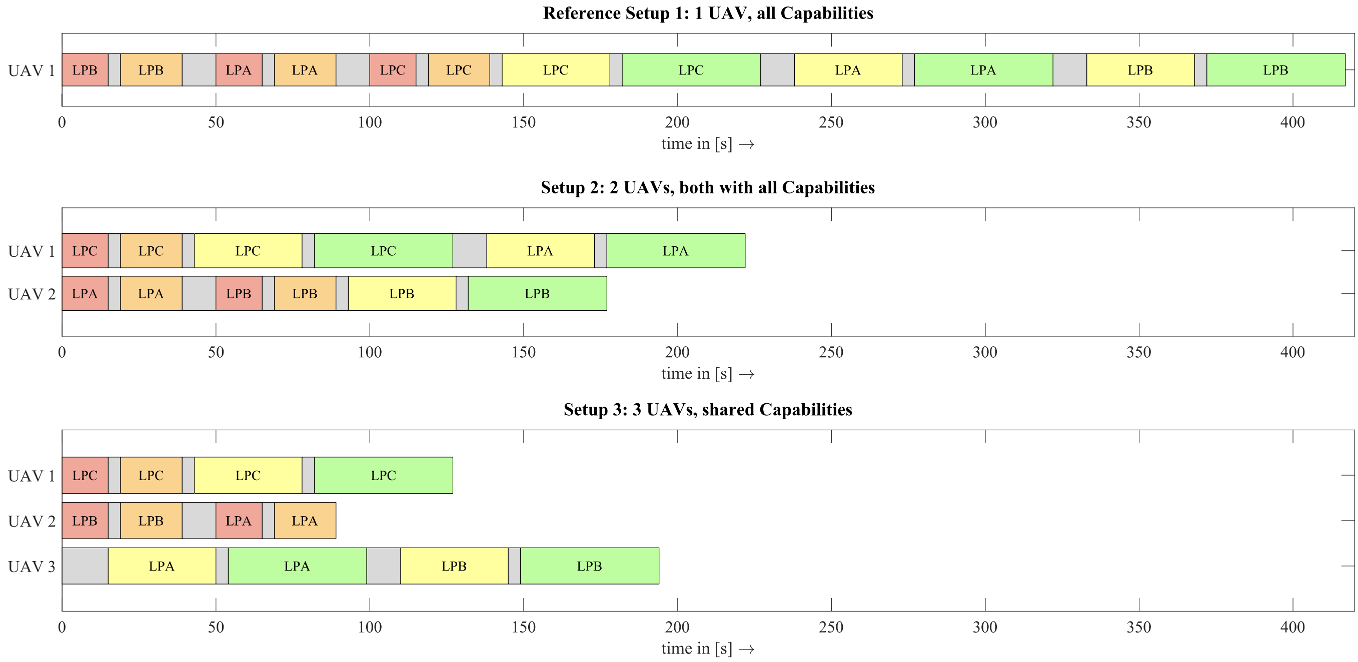

Fig. 13. Temporal visualization of the created PTAs. The person detection capability is marked in red, vehicle detection in orange, slope measurement in yellow, and obstacle detection in green. Gray boxes mark the transitions between the respective landing points.

VI. Conclusion and Future Work

In this article, we presented a concept for perception-oriented cooperation and planning for complex Multi-UAV reconnaissance missions in highly-dynamic environments. Consequently, the requirements and advantages of perception-oriented cooperation utilizing multiple, heterogeneous UAVs and the benefits of using a capability-centric approach for multi-UAV cooperation are discussed. Afterwards, first implementation aspects and architectural details of a prototype for such a system, POCA, are discussed, focusing on the integrated planning and scheduling components. Finally, first conducted experiments for the POCA prototype are presented and discussed, demonstrating promising results for multi-UAV cooperation, both in homogeneous and heterogeneous mission sensor and capability setups.

In the next steps, we will further optimize and test the prototype system, aiming to integrate it in a full mission H/C simulator available at our Institute. This will allow to measure the systems performance in more realistic and complex tactical situations, allowing to quantify the benefits of the proposed concept and evaluating system acceptance when interacting with military trained H/C pilots. Therefore, experimental operator-in-the-loop campaigns are planned for the beginning of 2017. On the other hand, several flight test campaigns are scheduled, to test the feasibility of perception-oriented cooperation for real UAVs. First, in summer 2016, verification tests of the *Information Demand Model* and its influence on the integrated sensor fusion and decision support mechanisms (cf. section IV.A) [30] will be conducted on a single multirotor MUAV. In addition, a multi-UAV flight campaign is scheduled for autumn/winter 2016, conducting a down-sized *Landing Zone Reconnaissance* on university grounds.

As an extension for the prototype presented in this article, a more sophisticated resource optimization algorithm should be implemented to optimize the number of UAVs and their payload configurations needed to fulfill the information demands for a given mission task in specified amount of time. Thereby, UAV redundancy could be avoided, freeing UAVs for tasks which are out of the scope of POCA.

Furthermore, a reliable mechanism to enable emerging capabilities in an ontology-based system (cf. IV.B) is still an open question which needs to be addressed this summer.

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