Multi-UAV Based Helicopter Landing Zone Reconnaissance

Information Level Fusion and Decision Support

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Abstract. This article presents an information fusion and decision-support system for the multi-UAV based landing zone reconnaissance and landing point evaluation in manned-unmanned teaming (MUM-T) helicopter missions. For this, numerous and heterogeneous data from variety of sensors must be gathered, fused and evaluated. However, payload capacity and on-board processing capabilities are often restricted. Thus, the teaming of multiple unmanned aerial vehicles (UAVs) offers a promising way to overcome these limitations and allows to benefit from heterogenous sensor payloads. Furthermore, measurement and sampling processes are never completely reliable. Hence, achieved observations must be interpreted very carefully, especially if the reliability of such functions is relatively low. Thus, the fusion system presented in this paper is based on a Bayesian network to specifically address this problem. Therefore, information needs of the pilots on safe landing zones are determined and required perceptive capabilities are derived. Consequently, reliability estimations of the applied perceptive capabilities are incorporated. Modelling aspects of the evaluation mechanism are explained and implications of incorporated export knowledge are set out. The feasibility of the implemented system is tested in an exemplary rescue mission, outlining the importance of incorporating automation reliability in automated decision-support systems.

Keywords: Information fusion · Bayesian networks · Decision support · Perception management · Manned unmanned teaming · Multi-UAV

1 Introduction

Landing the aircraft is one of the most challenging and dangerous tasks in aviation as pilots must perform many workload-intensive cognitive tasks simultaneously in a complex environmental situation. This is especially true for field landings of helicopters taking place in uncontrolled and unsafe areas as required e.g. during military search & rescue (SAR) operations like CASEVAC (casualty evacuation) or CSAR (combat search and rescue) [1]. In such situations, the pilots must not only cope with the landing procedure itself, but also with the vulnerability of the H/C during landing and take-off [2], making it necessary to reconnoiter the landing zone in advance.

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In this scope, one of the research topics in the R&D project CASIMUS (Cognitive Automated Sensor Integrated Unmanned Mission System) investigates the usage of multiple unmanned aerial vehicles (UAVs) to provide a manned two-seated transport helicopter (H/C) with up-to-date recce and surveillance data of potential landing zones in military SAR missions. To cope with the time-criticality of the latter, the UAVs are guided from on-board the H/C by the pilot-in-command (PiC) in a manned-unmanned-teaming (MUM-T) fashion to reduce typical command & control (C2) latencies and increase operational flexibility by employing higher levels of interoperability (LOI 4/5, [3]). Figure 1 depicts this functional principle, showing the H/C cockpit and three UAVs in a CASEVAC setting.

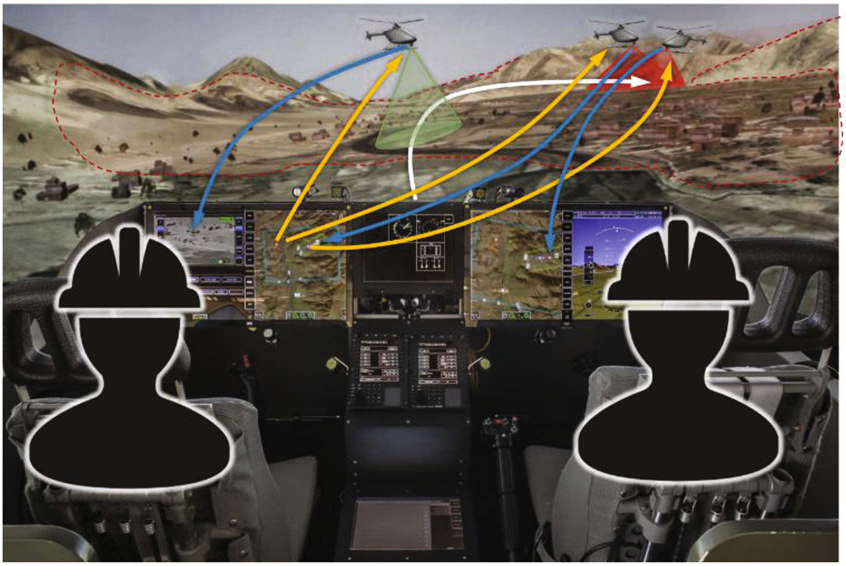

Fig. 1. MUM-T principle in our H/C mission simulator at the IFS. The PiC (left) is commanding multiple UAVs to reconnoiter its flying route (white) and mission-critical areas, i.e. the desired landing zone in the background (red). (Color figure online)

However, shifting the C2-loop into the cockpit comes with a cost. In contrast to legacy unmanned aerial system (UAS), the PiC must handle all UAV-related tasks in addition to his conventional task spectrum. Thus, a naïve MUM-T approach bears the risk to greatly increase crews workload which needs to be monitored and balanced in some way [4], either by the crew themselves or by an associate system on-board the H/C [5–7]. A promising way for workload mitigation is to adapt the task sharing between human and machine by adopting varying levels of automation (LOA, [8, 9]). Thus, to enable higher LOA, the UAVs must be capable to perform certain tasks in a (semi-)autonomous manner. Nevertheless, employing higher LOA bears the risk of automation-induced errors ("automation surprises"), complacency effects or other Trust-in-Automation issues [10–12]. To cope with such effects the behavior of the automated systems should be pilot-understandable and self-explanatory.

Therefore, this article describes a decision support system (DSS) for the multi-UAV based reconnaissance and assessment of helicopter landing zones to aid the H/C crew in picking a safe and suitable landing point during mission. The DSS is built upon the *Perception-Oriented Cooperation Agent* (POCA) [13], using a Bayesian network approach to evaluate possible landing points while providing self-explanation capabilities through diagnostic inference.

The remainder of this article is structured as follows: Sect. 2 sums up previous and related work in automated landing zone reconnaissance and agent self-explanation mechanisms. A general system is given in Sect. 2, stating requirements and providing operational principles for multi-UAV based landing zone reconnaissance. Section 4 describes the Bayesian network approach used in the landing point evaluation and self-explanation mechanisms. Preliminary evaluation results are presented in Sect. 5 along with some integration aspects in a full mission H/C simulator. Finally, Sect. 6 concludes the article and gives an outlook to further research and planned experiments.

2 Related Work

Landing Zone Reconnaissance or Landing Site Detection is a common problem in manned and unmanned aviation as well as in space exploration. In the following, some of the surveyed articles are reflected.

In manned aviation, landing zone reconnaissance often denotes the problem of flying in degraded visual environments (DVE). Therefore, Szoboszlay et al. [14–17] investigated the usage of LIDAR technology to detect a H/C landing site under DVE conditions and integrated the visualization in the helmet-mounted-display of the H/C pilot. They conducted research on necessary symbology and proofed their system in several flight test campaigns. A similar system was developed by Airbus [18], incorporating more sophisticated means of landing site and obstacle visualization.

Likewise, systems for the detection of safe landing points are presented in the unmanned aviation domain. Fitzgerald et al. [19, 20] combined basic computer vision algorithms with neural network based texture classifiers for surface type detection to select the best LS in a single image in case of UAV emergency. Patterson et al. developed a comparable system for the same problem in [21]. However, they are only relying on the detection of free areas in a single monocular image to determine a safe landing sites by using a simple edge extraction algorithm. In [22] their concept is extended to incorporate data obtained by other UAVs or using human operator input.

In the same scope, Coombes et al. [23] used a Multi Criteria Decision Making (MCDM) Bayesian Network (BN) for landing site selection. In their approach the proposed decision-making BN selects the emergency landing site based on General Aviation (GA) requirements on emergency landing sites.

Apart from that emergency LS detection problem, much work was done by Scherer et al. [24, 25] to determine a suitable landing site for an unmanned full-size helicopter. The proposed system heavily relies on a LIDAR-created 3D point cloud to create an elevation map allowing a rough evaluation of free areas. Besides the point cloud information, various other factors are considered, including terrain clearance, approach/depart paths, and wind direction. The selection itself is based on a *goodness* function, linearly combining the different selection criteria, incorporating operator preference in terms of weight adjustments.

Furthermore, space exploration missions demand a safe and reliably mechanism for automated landing site suitability determination during spacecraft descent. Therefore, Serrano [26] proposed a selection system based on Bayesian Networks (BN), integrated in a multi-sensor framework comprising of RADAR, LIDAR and camera sensors. Thereby, the presented decision system incorporated not only classical safety-related criteria, but also additional mission-specific factors, as for example the expected scientific return.

Our approach now incorporates sensors on multiple UAVs in the decision-making process. Therefore, the idea of modelling multiple decision criteria in a Bayesian Network [23] was picked up and extended to incorporate the perceptive reliability for landing point suitability determination.

3 Multi-UAV-Based Landing Zone Reconnaissance

Landing Zone Reconnaissance (LZR) denotes the task of reconnoitering a designated area (landing zone, LZ) to examine its suitability for take down, incorporating possible threats and physical characteristics of the landing zone. In this regard, performing LZR for a manned H/C in a full-fledged military rescue mission differs from the approaches presented before (cf. Sect. 2) as additional tactical and mission-critical aspects must be considered, most importantly the reliability of highly automated perceptive subfunctions [27, 28].

Figure 2 depicts an example setup for such a CASEVAC mission. There, a manned transport helicopter supported by three UAVs is deployed to rescue a group of persons in an unsafe operation area, whereby their last known position determines the designated landing zone. In this MUM-T setup, the UAVs shall reconnoiter potential landing points for the H/C suitable for a successful evacuation. Therefore, the UAVs must gather numerous and heterogenous data from the multiple potential landing points and evaluate them accordingly.

In the following, landing zone selection and landing point evaluation criteria are stated. Subsequently, the general concept for multi-UAV based LZR is presented.

3.1 Landing Zone Selection Criteria

Different regulations or heuristics exist for the definition of safe landing zones, both in civilian and in military applications. Basic requirements for conducting military LZR are stated in [1], leaving much space for national implementation, as for example the publicly available LZR regulations by the U.S. Army [29]. In general, several heterogeneous information needs must be incorporated when reconnoitering a landing zone: tactical, aeronautical, and meteorological. These needs come with inherent sequential ordering - for example, flight safety related considerations as obstacle situation can be neglected if tactical clearance has already failed.

Below, the current regulatory situation is summarized. Additional information gathered in consultative talks with German army aviators is incorporated.

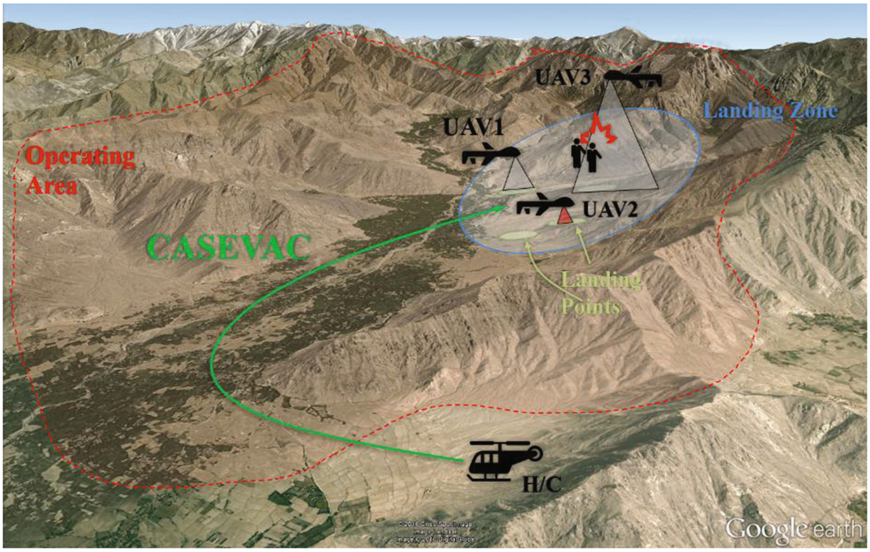

Fig. 2. CASEVAC example scenario: a manned transport helicopter aims in rescuing persons in an unsafe environment, guiding a team of three UAVs in a MUM-T fashion to determine the most suitable landing point in the designated landing zone (light blue). (Color figure online)

Tactical Considerations
The dominant concern for military LZR is information on the tactical situation and on mission-critical observations:

- **Safety.** Is the LZ safe or do threats exist? Are buried objects as EODs or mines present in the LZ? Are streets nearby, thus allowing enemy forces to reach the LZ fast?
- **Mission achievability.** Is the mission achievable from the LZ? How long will it take to reach the mission objective from the LZ? How long will the H/C be grounded and thus remain vulnerable?

Aeronautical Considerations
This contains requirements related to flight safety aspects in the LZ:

- **Landing zone size.** Is enough space for the actual H/C to touch down available?
- **Approach and departure directions.** Are obstructions in the approach or depart vectors present? Are conditions given limiting the approach/depart directions? What if the H/C is fully-loaded?
- **Obstacle situation.** Is the landing point itself free of obstacles? Smaller obstacles (debris, < 0.45 m) can be ignored;
- **Ground slope.** Does the slope exceed the H/C's limits? (However, the pilots can hover if ground slope is too high.)
- **Surface type and conditions.** What kind of surface will be encountered? Is there a risk to bog down? Are there brown-out or white-out conditions?

- **Ground solidity and load suitability.** Can a heavy transport H/C touch down on the desired landing point? Is the landing gear of the H/C suitable for landing in the desired area?

Meteorological Considerations
This refers to meteorological conditions in the LZ, directly influencing the H/Cs capability or risk for landing:

- **Cloud ceiling and visibility.** What is the ceiling level? Is it raining or do we have fog?
- **Density altitude.** What is the comparable density altitude at the LZ? Thus, is the H/C performant enough to operate in the LZ, even under high-load conditions?
- **Wind conditions.** What are wind velocities and directions? Thus, is landing into the wind possible? Do crosswind or tailwind conditions prevail?

3.2 Multi-UAV Concept

As depicted in Fig. 2 and stated in the prior section, landing zone reconnaissance requires the gathering and evaluation of numerous and heterogeneous data from (multiple) potential landing points in a designated area, the landing zone. Thus, the UAVs must provide a broad range of perceptive capabilities. However, UAVs are often restricted in terms of sensor payload capacity and on-board processing resources, effectively resulting in a limited set of capabilities. Hence, a single UAV might be insufficient to satisfy the perceptive requirements for a complex task as LZR. A promising way to overcome these limitations is the teaming of multiple UAVs by combining their capabilities in a cooperative manner, profiting from heterogeneous payload setups and varying platform characteristics as well as from task parallelization opportunities.

Consequently, we proposed the system concept of the Perception Oriented Cooperation Agent (POCA) in [13], extending the Sensor- & Perception Management (SPM) paradigm described in [30]. Thereby, it integrates environmental and platform self-adaption mechanisms from the SPM system while additionally incorporating perception planning and scheduling capabilities allowing to benefit from the multi-UAV set up stated above.

Figure 3 depicts the basic system concept. Here the operator (Pilot in Command) issues a “Landing Zone Recce” task to the system in a supervisory control manner, along with external constraints as the landing zone boundaries and available resources, e.g. available UAVs and thus available sensory equipment. This task is then analyzed by POCA to extract required perceptive actions, thus reflecting the information needs described in Sect. 3.1. These subtasks are interpreted as primary planning goals for the integrated task planning and scheduling mechanisms. During planning, external constraints, specific task requirements and available UAV capabilities extracted from a Perception Resource and Capability Ontology [31] are incorporated. Combining these, the Perception Planner creates a task agenda comprised of interleaved perceptual und navigational subtasks which are subsequently used to control and coordinate the UAVs underlying automation functions, i.e. the UAVs flight management system (FMS) and the SPMS. Thereby, plan generation itself follows a classical team-leader/team-member

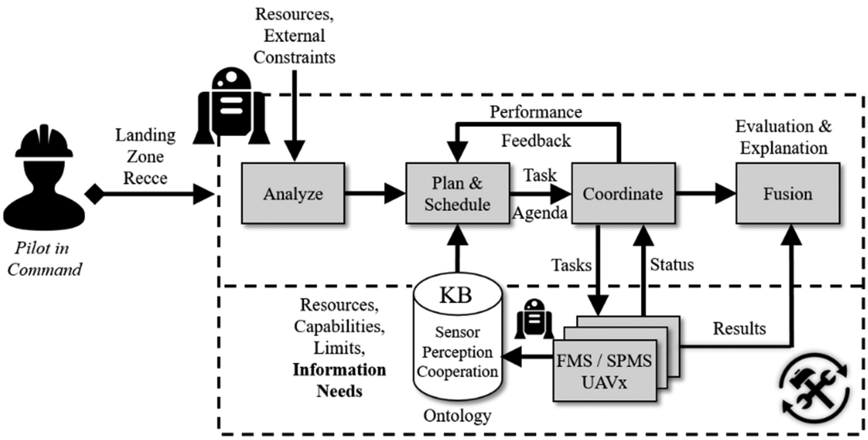

Fig. 3. Operational principle of POCA [13]. The notation is based on the work system notation in [33], thus the supervisory control arrow denotes both control and information feedback flow.

structure: the plan itself is generated by a designated team leading UAV whereas each team member is responsible for execution of the subtasks. During execution, the single POCA instances onboard the UAVs gather the results of their scheduled perception tasks, e.g. obstacle or vehicle detection. The results are transmitted to the leading UAV, which fuses and assesses the gathered results to derive a recommendation on the best suited landing zone.

This article focus on this latter step. In the following we describe an information-level fusion agent [32] for landing point evaluation based on causal Bayesian Inference, thereby incorporating perceptive reliability of the automated reconnaissance functions and expert knowledge on the underlying perceptive subtasks as well as their interconnections.

4 Bayesian Landing Point Evaluation

The fusion of heterogeneous information reflecting different physical phenomena, as needed for landing zone reconnaissance (cf. Sect. 3.1), invalidates the usage of classical low-level fusion methods such as Kalman filtering. Thus, a more abstract representation for such incommensurate data is needed to enable higher level fusion mechanisms on information level [32]. Hence, preprocessing and pre-assessment of the underlying sensory data is mandatory to enable the subsequent fusion mechanisms.

In POCA such preprocessing is realized by incorporating the SPM system of Hellert and Smirnov [34] (cf. Fig. 3), allowing it to rely on the integrated perceptive capabilities and high-level inference mechanisms to obtain semantically enriched results. Consequently, in POCA information-level fusion is applied on the percepts retrieved from the underlying SPM instances.

However, automated perception functions are imperfect by design and must be handled carefully, as such exhibit non-deterministic behavior and are prone to inherent uncertainties due to implementation weaknesses or changing operational environments [27, 28]. Thus, the outcome and results of the perceptive subtasks can best be expressed probabilistically. Therefore, to safely assess landing points in an examined landing zone a fusion mechanism is needed capable of handling these uncertainties.

In addition, the fusion architecture shall be able to incorporate expert knowledge on the information needs and provide means for extension and modularization allowing to adapt the fusion architecture on new or changed applications, e.g. civilian search & rescue missions.

Considering the above, we propose the usage of a *Bayesian Network* (BN) [35] to explicitly model knowledge on the interdependencies between the information needs in a fusion graph. Thereby, the conditional probabilities of the network are automatically adjusted during runtime.

In the following, some BN fundamentals are stated. Afterwards, our approach to evaluate landing points using a BN is explained in Subsect. 4.2.

4.1 Bayesian Network Fundamentals

BNs are a commonly used graphical tool for knowledge representation and reasoning under uncertainty in decision-making intelligent systems, allowing the incorporation of explicit modelled and elicited knowledge of domain experts.

More generally, a BN is a *Directed Acyclic Graph* (DAG) in which the nodes represent the random variables of interest and the arcs the causal relation between these nodes, thus reflecting the conditional dependency between the nodes. In addition, a BN assumes conditional independency between nodes on the same level, meaning that any node x_i with the parents y_i is conditionally independent from any other variable except of its descendants z_i. Thereby, the graphical representation of BNs provides an unambiguous and relatively simple way of representing this independency between variables.

Figure 4 visualizes this independency topology and shows the three fundamental connection types for nodes in a BN, forming the basic conditional probabilities for BNs. Thus, a joint probability distribution (JPD) for a BN with the nodes $X_i = \{x_i, \ldots, x_n\}$ can be derived using Bayes' chain rule:

$$P(x_1, \ldots, x_n) = P(x_n | x_{n-1} \ldots x_1)\, P(x_{n-1} | x_{n-2} \ldots x_1) \ldots P(x_2 | x_1)\, P(x_1) \qquad (1)$$

$$P(x_1, \ldots, x_n) = \prod\nolimits_{i=1}^{n} P(x_i | x_{i-1}, \ldots, x_1) \qquad (2)$$

Incorporating the independency assumption above with the parents $Y_i = \{y_i, \ldots, y_n\}$, Eq. (2) could be simplified to:

$$P(x_1, \ldots, x_n) = \prod\nolimits_{i=1}^{n} P(x_i | y_i(X_i)) \qquad (3)$$

This simplified JPD exhibits an important feature of BNs: since the node x_i in a BN is only dependent on the state of its parents y_i instead of depending on arcs to each other node $x_j \in X_i$ (which requires 2^n arcs), the number of parameters needed to model or learn a BN can be reduced drastically.

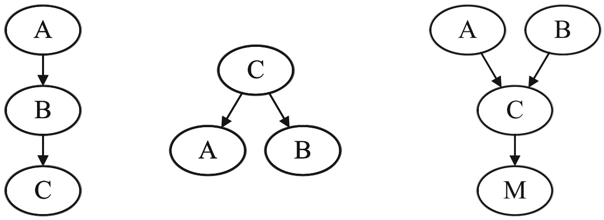

Fig. 4. Basic elements of BNs: serial connection (left), diverging connection (middle) and converging connection (right).

With *Influence Diagrams* (ID) a generalization for BNs exists to allow the application on decision-making problems [36]. IDs add two special types of nodes in the BN notation (*decision* and *utility* nodes), whereas random variables are called *chance* nodes. Thereby, a decision node is a controllable point where a mutual exclusive action $A = \{a_1, \ldots, a_n\}$ influences the probability distributions off connected random variables. Utility nodes represent the value or outcome of a decision. In multi-criteria decision-making (MCDM) problems, criteria nodes denote chance nodes directly influencing a utility node [37].

4.2 Landing Point Evaluation Using a Bayesian Network

As described earlier, various criteria are needed to safely assess and evaluate a landing zone and to pick a safe and reliable landing point. Thus, it comes naturally to formulate the landing point evaluation problem in terms of multi-criteria decision-making (MCDM).

In the following our approach for a MCDM Bayesian Network to evaluate landing points, following the notations in [37]. The single components of the network are explained, providing insights on implementation details. Figure 5 visualizes the DAG of the developed BN while Table 1 lists all nodes with their possible, discretized states and associated node types.

Essentially, the requirements in Sect. 3.1 can be summarized in two criteria: helicopter safety and mission achievability. Consequently, the utility end-node "Landing Point Quality" in Fig. 5 is only influenced by the two reflecting criteria nodes "Landing Point Safety" and "Mission Achievability", which combine the conditional probabilities tables (CPT) of the underlying information needs encoded in the single chance nodes. Effectively, the utility node implements a weighting function of the two mission-influencing criteria, thereby prioritizing helicopter safety.

In our current implementation, mission achievability is only influenced by the geographical distance to the mission objective (e.g. the distance to the last known position of the persons to be rescued in the example in Fig. 2). In contrast, helicopter safety is influenced by a broad variety of parameters.

Expert knowledge on the interconnections between information needs is encapsulated semantically in the structure of the net in Fig. 5 and the CPT of the criteria nodes. Thus, to ease the compilation of the CPT for the "Landing Point Safety" node, several intermediate or hidden nodes were used.

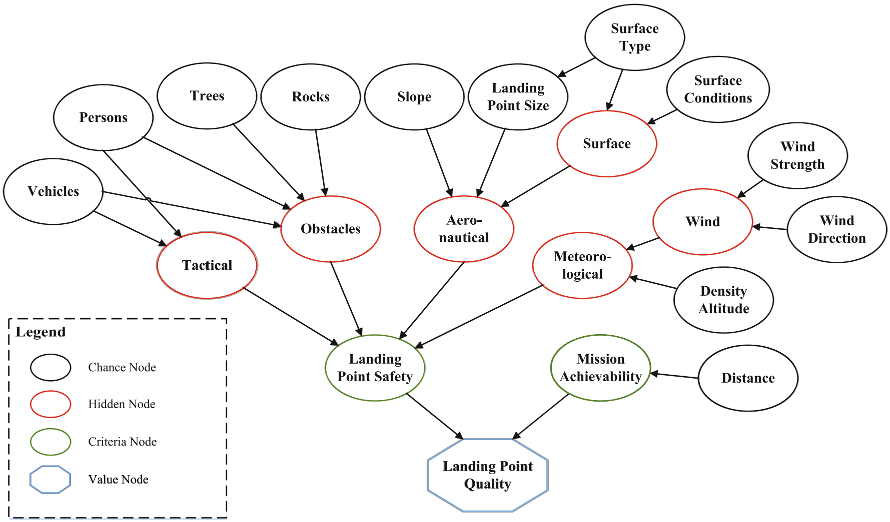

Fig. 5. DAG structure for the proposed landing point evaluation network.

Table 1. List of all nodes, their discrete states and the associated node type in the proposed landing point evaluation network. Nodes are sorted according their related type.

Node	States	Node type
Vehicles	Present; Absent	Chance
Persons	Present; Absent	Chance
Trees	Present; Absent	Chance
Rocks	Present; Absent	Chance
Slope	Very High; High; Medium; Low; None	Chance
Landing point size	Tiny; Small; Medium; Big	Chance
Surface type	Grass; Concrete; Swamp; Sand; Snow	Chance
Surface conditions	Dry; Wet	Chance
Wind strength	Strong; Medium; Weak; None	Chance
Wind direction	Head; Cross; Tail	Chance
Density altitude	Comparable; Different	Chance
Distance	Close; Medium; Out of Range	Chance
Tactical	Safe; Unsafe	Hidden
Obstacles	Present; Absent	Hidden
Surface	Good; Bad	Hidden
Aeronautical	Good; Bad	Hidden
Meteorological	Safe; Unsafe; Dangerous	Hidden
Safe landing point	Safe; Unsafe	Criteria
Mission achievability	Possible; Critical; Impossible	Criteria
Landing point quality	Quality percentage (0–100)	Value

The chance nodes represent the sensed input to the proposed fusion system. CPT values are expressed probabilistically to reflect inaccurate measurements and nondeterministic behavior of the underlying processing algorithms. Quantitative values for the CPTs are constantly updated during mission, thereby incorporating potentially varying automation reliabilities for the actually selected perceptive functions, which can be adjusted during mission due to environmental changes [28]. Perceptive tasks with quantifiable results, for example vehicle or obstacle detection are heavily condensed (cf. Table 1). Thus, the insignificance for the safety assessment is expressed whether there are one or ten potentially dangerous objects at a landing point. Continuously valued results, e.g. the slope in degrees, are discretized accordingly to enable incorporation in the BN structure [38]. In addition, the influence of the helicopter type on the aeronautical and meteorological criteria is explicitly modelled in the BN, using a decision node. However, for the sake of greater clarity this is neither depicted in Fig. 5 nor listed in Table 1.

Finally, causal reasoning is applied using the SMILE engine[1] [39] to gain an actual quality value for the currently processed landing point.

5 Results and Discussion

To demonstrate the feasibility of the presented landing point evaluation and fusion mechanism, an example use case scenario for landing zone reconnaissance was created. The tactical situation for the unreconnoitered landing zone in the test setup is depicted in Fig. 6, embedded in the bigger scope of a full CASEVAC mission outlined before (cf. Sect. 3). There, a group of persons must be rescued in an unsecure and potentially dangerous area, whereby their last position is known, thus determining the rescue area and the designated landing zone. The rescuing H/C is supported by a team of three UAVs, providing perceptive capabilities for landing zone reconnaissance.

The parameters for each chance node in the test scenario are shown in Table 2. To reflect state crossings, a soft threshold was used to determine the discrete states. For example, the surface type of LPB is not clearly determinable. To account for such ambiguities, the CPTs of the continuous attributes may contain factorized values. Thus, the surface type of LPB is set to 85% of grassland and 15% of sand, reflecting an area with a rough grass cover containing some sandy spots.

Not depicted in Table 2 are the probabilistic influences of the used perceptive capabilities. The values for the appropriate measurements are applied to the single chance nodes individually. We used reliability values for perceptive algorithms available in our SPM systems [30, 34]:

- Person detection was performed using an infrared camera based support vector machine (SVM) classifier, having a relatively low reliability of 0.66 [27].
- For vehicle detection a deformable part model (DPM) with a trained SVM classifier on electro-optical images was deployed, having a reliability of 0.93 [28].

[1] BayesFusion, LLC, http://www.bayesfusion.com/.

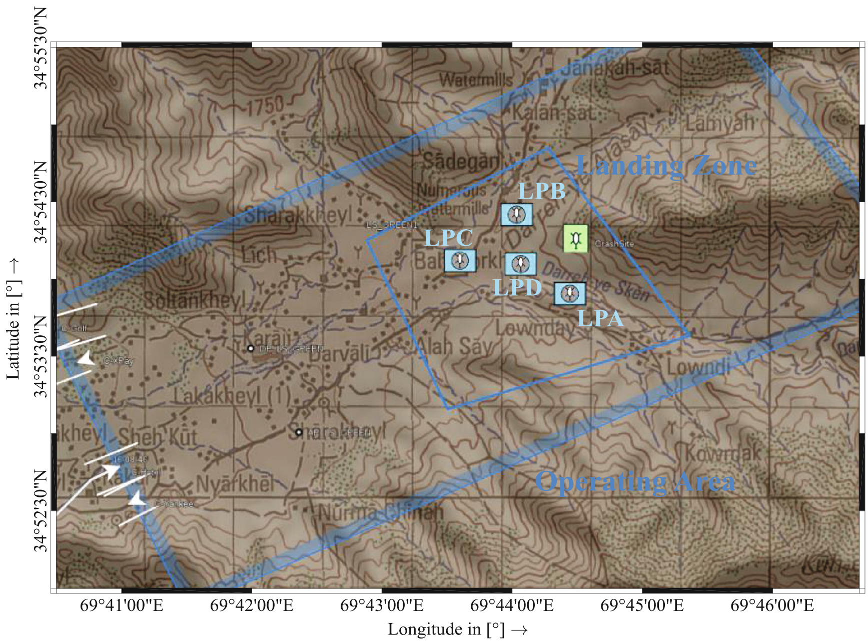

Fig. 6. Test setup for landing zone reconnaissance in a CASEVAC scenario. The landing zone contains four landing points LPA, LPB, LPC and LPD to be reconnoitered and evaluated.

Table 2. Discrete parameters of the chance nodes for the single landing points. A soft threshold was applied, thus factorized values reflect transition between the discrete states.

	LPA	LPB	LPC	LPD
Vehicles	Present	Absent	Absent	Absent
Persons	Absent	Absent	Absent	Absent
Trees	Present	Absent	Present	Absent
Rocks	Absent	Absent	Absent	Present
Slope	Low	Low	Low	Medium
LP size	Medium	Big	Big	Small
Surface type	0.5 Grass 0.5 Sand	0.85 Grass 0.15 Sand	0.3 Grass 0.7 Sand	Grass
Surface conditions	Dry	Dry	Dry	Dry
Wind strength	Medium	Weak	Medium	Weak
Wind direction	0.3 Cross 0.7 Tail	0.8 Head 0.2 Cross	0.3 Head 0.7 Cross	Head
Density altitude	Comparable	Comparable	Comparable	Comparable
Distance	Close	Close	Medium	Close

- Rock and tree detection as well as landing point and slope measurement are based on LIDAR processing, having a measurement and detection reliability of 0.98.
- Surface determination is based on GIS data for which a deterministic value is assumed. Nevertheless, the nodes incorporate soft thresholding as described above.
- The same applies for the meteorological nodes, incorporating data from a weather information service.
- Distance measurement is based on a simple estimation of the walking distance, combining Euclidean distance and the movement speed of persons by foot.

Table 3. Evaluation results and quality values for the single landing points.

	Safety	Achievability	Quality
LPA	Unsafe: 7%	Possible: 100%	69%
LPB	**Safe: 60%**	**Possible: 100%**	**59.9%**
LPC	Unsafe: 21%	Critical: 50%	18.1%
LPD	Unsafe: 18%	Possible: 100%	17.5%

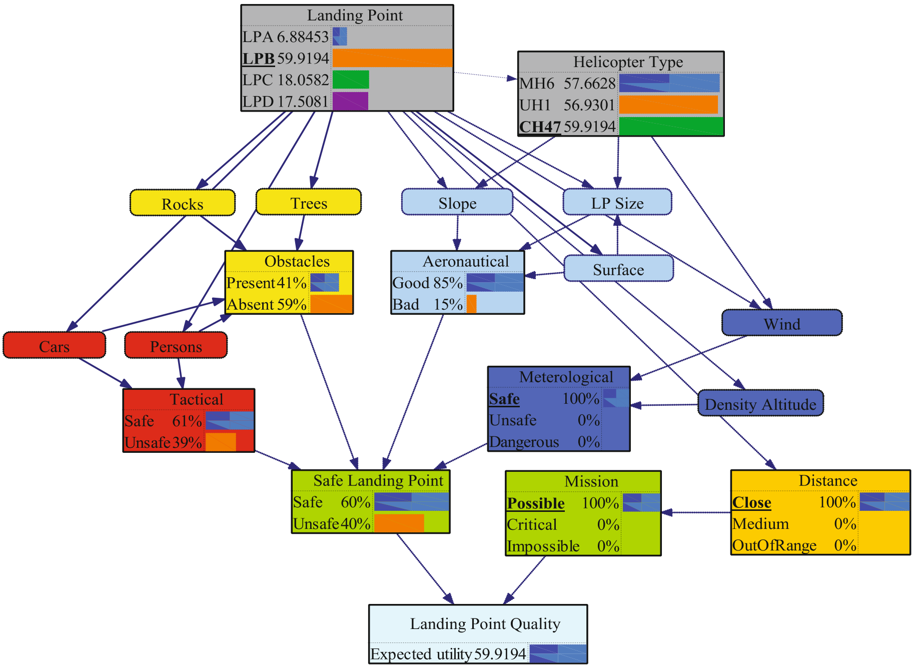

Fig. 7. Results of the landing point evaluation for LPB, modelled in GeNIe [36]. Chance nodes belonging in the same group are color-coded: (tactical), yellow (obstacle), light blue (aeronautical) and dark blue (meteorological). Submodels (e.g. "Cars" or "Persons") were used to apply the automation reliabilities on the CPTs of the appropriate chance nodes. Due to modelling and test purposes in GeNIe, an additional decision node ("Landing Points", gray) exist. (Color figure online)

The quality of each landing point was determined assuming a Boeing CH-47 as rescuing helicopter. The criteria values and estimated quality inferred are summarized in Table 3. The network selects LPB as recommended landing point for the rescue mission as it has the highest quality assessment of 59.9%. Although this value seems to be rather low, it characterizes the importance of incorporating automation reliability in the decision-making process when applying highly-automated sensor based systems.

Figure 7 displays the Bayesian network modelled in GeNIe [39] with inferred values for the winning landing point LPB. As it can be seen, the quality assessment is mainly based on the safety estimation. Thus, the usage of the relatively unreliable person detector described above heavily influences the quality estimation, following Bayes rule for determining the JPD as shown in Eq. (3).

A naïve interpretation of the parameters in Table 2, ignoring automation reliability, might have led to the false impression of safety. Consequently, a decision-support mechanism for highly automated reconnaissance systems must consider possible drawbacks when presenting results and providing suggestions to human operators.

Thus, the presentation of the evaluation results and final recommendation shall express the uncertain nature of the decision-making process and allow the pilot to scrutinize the derived result. Our current approach for presenting the evaluation results on recommendation level uses a color-coded traffic-light representation as shown in Fig. 8. Whenever the pilot chooses to receive more details on the decisions rational, information on the most influencing factors are presented (not depicted).

Fig. 8. Tactical map visualization of the landing point evaluation results displayed in the multi-function-display of our H/C simulator. The landing point quality is depicted color-coded in an easy-to-understand traffic-light representation.

6 Conclusion

The safe and reliable reconnaissance of a helicopter landing zone requires the gathering of various heterogenous data from potential landing points which must be fused and evaluated accordingly. Therefore, such an evaluation and fusion mechanisms was presented in this paper based on a multi-criteria decision-making Bayesian Network. The proposed BN incorporates expert knowledge on LZR information needs and a probabilistic representation of the automation reliability, adapted online during mission. Bayesian inference is applied to estimate the landing point quality whenever new reconnaissance data comes available.

The feasibility of presented fusion agent was demonstrated on a given example and obtained results are demonstrated and discussed, emphasizing the importance of incorporating automation reliability in the decision-making process. Probabilistic inclusion of the reliability value in a Bayesian Network as presented here provides a promising way to deal with such influences and resulting automation over trust issues. An easily understandable visualization concept for the evaluation results in the multi-function-display of a H/C cockpit is presented.

Nevertheless, to avoid distrust effects, further work is required to increase the overall system reliability. For example, the automated system can apply additional fusion mechanisms to fulfill a perceptive requirement more reliably, e.g. by combining multiple perception algorithms in the person detection processing chain. Another promising approach is to incorporate inputs of a human operator in cases when the overall system reliability is too low to be trusted [7].

Furthermore, additional work is required on the result presentation to enable the crew to verify the reconnaissance results by themselves and thus to better understand the landing point recommendation.

Next steps will quantifiably determine benefits and overall system acceptance when interacting with military trained H/C pilots. Therefore, an experimental operator-in-the-loop campaign in the full mission MUM-T H/C simulator are planned for summer 2017. In addition, technological readiness for multi-UAV based perception will be evaluated in a down-sized Landing Zone Reconnaissance experiment at university grounds in summer too.

References

1. NATO Standardization Agency: STANAG 2999 - Use of Helicopters in Land Operations Doctrine ATP-49(F) (2012)
2. Hastert, P.L.: Operation Anaconda: perception meets reality in the hills of Afghanistan. Stud. Confl. Terror. **28**, 11–20 (2005)
3. NATO Standardization Agency: STANAG 4586 - Standard Interface of UAV Control System (UCS) for NATO UAV Interoperability (2012)
4. Schulte, A., Donath, D., Honecker, F.: Human-system interaction analysis for military Multi-RPA pilot activity and mental workload determination. In: IEEE International Conference on Systems, Man, and Cybernetics (SMC 2015), pp. 1375–1380 (2015)

5. Strenzke, R., Uhrmann, J., Benzler, A., Maiwald, F., Rauschert, A., Schulte, A.: Managing cockpit crew excess task load in military manned-unmanned teaming missions by dual-mode cognitive automation approaches. In: AIAA Guidance, Navigation, and Control Conference (2011)
6. Honecker, F., Brand, Y., Schulte, A.: A task-centered approach for workload-adaptive pilot associate systems. In: The 32nd EAAP Conference, Cascais, Portugal (2016)
7. Ruf, C., Stütz, P.: Model-driven sensor operation assistance for a transport helicopter crew in manned-unmanned teaming missions: selecting the automation level by machine decision-making. In: Savage-Knepshield, P., Chen, J. (eds.) Advances in Human Factors in Robots and Unmanned Systems. AISC, vol. 499, pp. 253–265. Springer, Cham (2017). doi:10.1007/978-3-319-41959-6_21
8. Parasuraman, R., Sheridan, T.B., Wickens, C.D.: A model for types and levels of human interaction with automation. IEEE Trans. Syst. Man Cybern. Part A Syst. Hum. **30**, 286–297 (2000)
9. Sheridan, T.B.: Adaptive automation, level of automation, allocation authority, supervisory control, and adaptive control: distinctions and modes of adaptation. IEEE Trans. Syst. Man Cybern. Part A Syst. Hum. **41**, 662–667 (2011)
10. Sarter, N.B., Woods, D.D., Billings, C.E.: Automation surprises. In: Salvendy, G. (ed.) Handbook of Human Factors and Ergonomics, pp. 1926–1943. Wiley (1997)
11. Parasuraman, R., Molloy, R., Singh, I.L.: Performance consequences of automation-induced "Complacency". Int. J. Aviat. Psychol. **3**, 1–23 (1993)
12. Baker, A.L., Keebler, J.R.: Factors affecting performance of human-automation teams. In: Savage-Knepshield, P., Chen, J. (eds.) Advances in Human Factors in Robots and Unmanned Systems. AISC, vol. 499, pp. 331–340. Springer, Cham (2017). doi:10.1007/978-3-319-41959-6_27
13. Schmitt, M., Stuetz, P.: Perception-oriented cooperation for multiple UAVs in a perception management framework: system concept and first results. In: 2016 IEEE/AIAA 35th Digital Avionics Systems Conference (DASC), Sacramento, California, USA, pp. 1–10. IEEE (2016)
14. Szoboszlay, Z.P., Turpin, T.S., Mckinley, R.A.: Symbology for brown-out landings: the first simulation for the 3D-LZ program. In: 65th American Helicopter Society Annual Forum 2009 (AHS65). American Helicopter Society International (AHS), Ft. Worth, Texas, USA (2009)
15. Szoboszlay, Z.P., McKinley, R.A., Braddom, S.R., Harrington, W.W., Burns, H.N., Savage, J.C.: Landing an H-60 helicopter in brownout conditions using 3D-LZ displays. In: 66th American Helicopter Society Annual Forum 2010 (AHS66). American Helicopter Society International (AHS), Phoenix, Arizona, USA (2010)
16. Harrington, W., Braddom, S., Savage, J., Szoboszlay, Z., McKinley, R.A., Burns, H.N.: 3D-LZ Brownout landing solution. In: 66th American Helicopter Society Annual Forum 2010 (AHS66). American Helicopter Society International (AHS), Phoenix, Arizona, USA (2010)
17. Szoboszlay, Z.P., Fujizawa, B.T., Ott, C.R., Savage, J.C., Goodrich, S.M., McKinley, R.A., Soukup, J.R.: 3D-LZ flight test of 2013: Landing an EH-60L Helicopter in a brownout degraded visual environment. In: 70th American Helicopter Society Annual Forum 2014 (AHS70). American Helicopter Society International (AHS), Montréal, Québec, Canada (2014)
18. Airbus Defence & Space: White Paper: Solving the problem of flying in DVE for helicopter pilots (2014)

19. Fitzgerald, D., Walker, R.: Classification of candidate landing sites for UAV forced landings. In: AIAA Guidance, Navigation, and Control Conference and Exhibit. American Institute of Aeronautics and Astronautics, San Francisco, California, USA (2005)
20. Fitzgerald, D., Walker, R., Campbell, D.: A Vision based forced landing site selection system for an autonomous UAV. In: 2005 International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), Melbourne, Australia, pp. 397–402. IEEE (2005)
21. Patterson, T., McClean, S., Parr, G., Morrow, P., Teacy, L., Nie, J.: Integration of terrain image sensing with UAV safety management protocols. In: Par, G., Morrow, P. (eds.) Sensor Systems and Software, pp. 36–51. Springer, Heidelberg (2011)
22. Patterson, T., McClean, S., Morrow, P., Parr, G.: Modelling safe landing zone detection options to assist in safety critical UAV decision making. Procedia Comput. Sci. **10**, 1146–1151 (2012)
23. Coombes, M., Chen, W.-H., Render, P.: Site selection during unmanned aerial system forced landings using decision-making Bayesian networks. J. Aerosp. Inf. Syst. **13**, 491–495 (2016)
24. Scherer, S., Chamberlain, L., Singh, S.: Online assessment of landing sites. In: AIAA Infotech@aerosp., pp. 1–14 (2010)
25. Scherer, S., Chamberlain, L., Singh, S.: Autonomous landing at unprepared sites by a full-scale helicopter. Rob. Auton. Syst. **60**, 1545–1562 (2012)
26. Serrano, N.: A Bayesian framework for landing site selection during autonomous spacecraft descent. In: 2006 IEEE/RSJ International Conference on Intelligent Robots and Systems, Beijing, China, pp. 5112–5117. IEEE (2006)
27. Russ, M., Stuetz, P.: Application of a probabilistic market-based approach in UAV sensor & perception management. In: 2013 16th International Conference on Information Fusion (FUSION 2013), Istanbul, pp. 676–683 (2013)
28. Hellert, C., Stütz, P.: Performance prediction and selection of aerial perception functions during UAV missions. In: 2017 IEEE Aerospace Conference, Big Sky, Montana. IEEE (2017, in press)
29. U.S. Department of the Army: Attack Reconnaissance Helicopter Operations (FM 3-04.126) (2007). http://usacac.army.mil/sites/default/files/misc/doctrine/CDG/cdg_resources/manuals/fm/fm3_04x126.pdf
30. Russ, M., Stütz, P.: Airborne sensor and perception management: a conceptual approach for surveillance UAS. In: Proceedings of the 15th International Conference on Information Fusion (FUSION 2012), Singapore, pp. 2444–2451. IEEE (2012)
31. Smirnov, D., Stütz, P.: Use case driven approach for ontology-based modeling of reconnaissance resources on-board UAVs using OWL. In: 2017 IEEE Aerospace Conference, Big Sky, Montana, USA. IEEE (2017, in press)
32. Hall, D.L., Llinas, J.: Multisensor data fusion. In: Handbook of Multisensor Data Fusion, pp. 1–14. CRC Press (2008)
33. Schulte, A., Donath, D., Lange, D.S.: Design patterns for human-cognitive agent teaming. In: Harris, D. (ed.) EPCE 2016. LNCS (LNAI), vol. 9736, pp. 231–243. Springer, Cham (2016). doi:10.1007/978-3-319-40030-3_24
34. Hellert, C., Smirnov, D., Russ, M., Stuetz, P.: A high level active perception concept for UAV mission scenarios. In: Deutscher Luft- und Raumfahrtkongress 2012, pp. 1–9. Deutsche Gesellschaft für Luft- und Raumfahrt - Lilienthal-Oberth e.V., Berlin (2012)
35. Pearl, J.: Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference. Morgan Kaufmann Publishers, San Mateo (1988)
36. Russell, S.J., Norvig, P.: making simple decisions. In: Artificial Intelligence: A Modern Approach, 2nd edn., pp. 626–627. Prentice Hall (2010)

37. Watthayu, W., Peng, Y.: A Bayesian network based framework for multi-criteria decision making. In: Proceedings of the 17th International Conference on Multiple Criteria Decision Analysis, Whistler, B.C., Canada (2004)
38. Russell, S.J., Norvig, P.: Probabilistic Reasoning. In: Artificial Intelligence: A Modern Approach, 3rd edn., pp. 510–565. Prentice Hall (2010)
39. Druzdzel, M.J.: SMILE: structural modeling, inference, and learning engine and GeNIe: a development environment for graphical decision-theoretic models. In: Proceedings of the Sixteenth National Conference on Artificial Intelligence and the Eleventh Innovative Applications of Artificial Intelligence Conference Innovative Applications of Artificial Intelligence (AAAI 1999/IAAI 1999), pp. 902–903. AAAI Press, Menlo Park (1999)