Symbolic Logic Framework for Situational Awareness in Mixed Autonomy

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List of Abbreviations

ACAS	Airborne Collision Avoidance System
ADS-B	Automatic Dependent Surveillance - Broadcast
ACAS	Airborne Collision Avoidance System
AGL	Above Ground Level
AI	Artificial Intelligence
ATC	Air Traffic Control
ATM	Air Traffic Management
BVLOS	Beyond Visual Line Of Sight
CA	Collision Avoidance
ConOps	Concept of Operations
DAA	Detect And Avoid
DAIDALUS	Detect and Avoid Alerting Logic for Unmanned Systems
EIC	European Innovation Council
FAA	Federal Aviation Administration
FMS	Flight Management System
MAS	Multi Agent System
MDP	Markov Decision Process
MOPS	Minimum Operational Performance Standards
NA	Not Applicable
NASA	National Aeronautics and Space Administration
NMAC	Near Mid-Air Collision
NOTAM	Notice to Airmen
OSED	Operational Services and Environment Definition
POMDP	Partially Observable Markov Decision Process
RA	Resolution Advisory
RP	Remote Pilot
RPIC	Remote Pilot In Command
RWC	Remain Well Clear
SA	Situational Awareness
SESAR	Single European Sky Air Traffic Management Research
STM	Surveillance and Tracking Module

sNMAC	sUAS Near Mid-Air Collision
sUAS	small Unmanned Aircraft System
TA	Traffic Advisory
TCAS	Traffic alert and Collision Avoidance System
TRM	Threat Resolution Module
UA	Unmanned Aircraft
UAM	Urban Air Mobility
UAS	Unmanned Aircraft System
USS	UAS Service Supplier
UTM	UAS Traffic Management
VLL	Very-Low Level

1 Introduction

1.1 SymAware: High-level description of the project

SymAware addresses the fundamental need for a new conceptual framework for awareness in multi-agent systems that is compatible with the internal models and specifications of robotic agents and that enables safe simultaneous operation of collaborating autonomous agents and humans. The goal of SymAware is to provide a comprehensive framework for situational awareness to support sustainable autonomy via agents that actively perceive risks and collaborate with other robots and humans to improve their awareness and understanding while fulfilling complex and dynamically changing tasks. The SymAware framework will use compositional logic, symbolic computations, formal reasoning, and uncertainty quantification to characterise and support situational awareness of MAS in its various dimensions, sustaining awareness by learning in social contexts, quantifying risks based on limited knowledge, and formulating risk-aware negotiation of task distributions. These goals will be achieved in SymAware through the following technical objectives:

1. Logical characterization of awareness using symbolic methods;
2. Quantifying the symbolic reasoning for awareness with spatial and temporal ingredients for decision making;
3. Risk awareness via quantified knowledge;
4. Quantifying and communicating knowledge awareness;
5. Demonstrating awareness engineering in aviation and automotive use cases; and
6. Identifying requirements for ethical and trustworthy awareness in human-agent interaction.

The objectives of SymAware address the “Awareness Inside” Challenge of the European Innovation Council (EIC) by extending and formalizing human-based models of situational awareness and by providing a novel conceptual situational awareness framework for MASs that encompasses logical characterisation and integrative formal reasoning of interdependent awareness dimensions including knowledge, spatiotemporal, risk and social dimensions. This will support transitioning to safe mixed operation of autonomous agents and humans.

Figure 1 shows a schematic view of the SymAware new cognitive awareness architecture. Together the objectives of this proposal will achieve the depicted situational awareness for multi-agent settings in which the situational awareness is related to the different awareness dimensions and to contemporary methods for probabilistic modelling, perception, estimation, and (data-driven) computation.

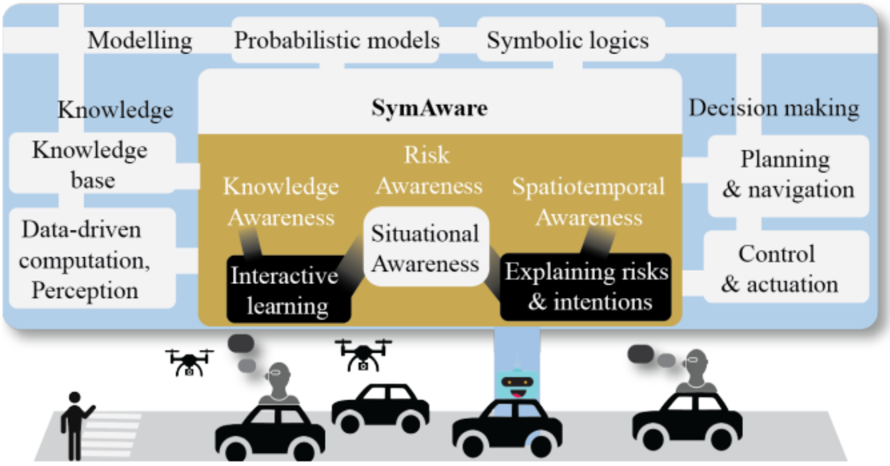

Figure 1. The novel cognitive architecture developed in SymAware

Figure 2 shows the main technical work packages of SymAware. The comprehensive framework of situational awareness and its logical characterisation (Objective 1) will be developed in WP1. The spatiotemporal awareness of Objective 2 will be studied in WP2. Risk and knowledge awareness (Objectives 3 and 4) will be studied in WP3 and WP4, respectively. The automotive and aviation use cases (Objective 5) will be developed in WP5. Finally, the human-robot interaction and the ethical requirements (Objective 6) will be studied in WP6.

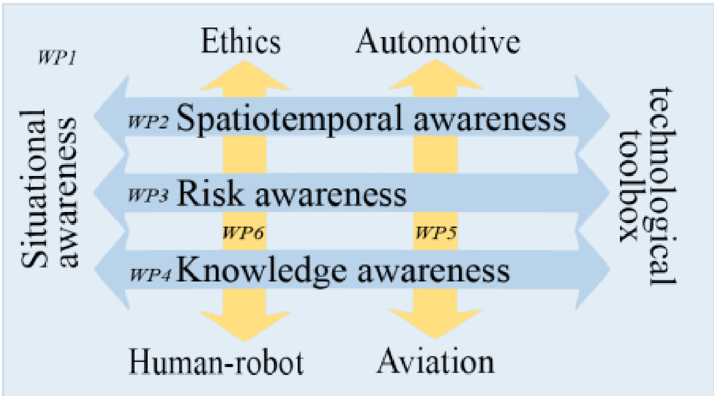

Figure 2. The main (technical) work packages of SymAware

1.2 Purpose and contents of this report

This report is the first deliverable of WP5 on the automotive and aviation use cases. Its purpose is to develop an awareness-based operational concept for unmanned aircraft system (UAS) operations and their traffic management (UTM). This development is based on initial work on situation and risk awareness in WP1 [1]. The operational concept description includes the scoping of the environment, the types of operations, and situational awareness and risk awareness of agents in the operations. The operational concept will form the foundation for the development of detailed agent-based models that will allow simulation-based analysis of distributed situation and risk awareness in UTM operations.

This report is structured in the following way:

- Section 1 describes the SymAware project and the purpose of the current report.
- Section 2 provides an overview of concepts and high-level model for situational and risk awareness in multi-agent sociotechnical systems.
- Section 3 provides a review of the state-of-the-art of operational concepts for UAS operations at low altitudes and supporting detect and avoid (DAA) systems.
- Section 4 describes the operational concept
- Section 5 provides the conclusions and perspective on follow-up work.

2 Situational awareness concepts & models

This chapter provides a high-level overview of situational awareness concepts and models. Section 2.1 provides a concise summary of key concepts for situational awareness, risk awareness, and agent-based modelling. Section 2.2 presents basic situational awareness components of agents (human operators, technical systems), describing awareness of states and intents. Section 2.3 describes processes that agents may use for updating of situational awareness. Section 2.4 extends the situational awareness modelling by inclusion of uncertainty and risk awareness by agents. Section 2.5 describes awareness-based acting and control by agents, describing adapted intents to be achieved by agents in efforts to reduce risks to acceptable levels. Finally, Section 2.6 provides an integrated overview of the situational awareness components and processes presented.

2.1 Background

2.1.1 Situational awareness concepts

In the field of safety and human factors a well-known definition of situational awareness is by Endsley [2]: ‘Situation awareness is the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future’. In this definition, situational awareness is a dynamic state of knowledge which discerns three levels: (1) perception of elements in the environment, (2) comprehension of the current situation, (3) projection of the future status. The process of achieving, acquiring and maintaining situational awareness is referred to as situational assessment [2]. For teams of interacting humans, the situational awareness states of the humans involved depends on team processes such as communication and coordination, in addition to the cognitive processes as perception, comprehension and projection.

For joint cognitive systems, comprising humans and technical systems, the concept of distributed situational awareness has been proposed [3, 4]. In this context situational awareness is defined as ‘activated knowledge for a specific task, at a specific time within a system’, and can be held by humans and technical systems. In line with distributed cognition theory, distributed situational awareness is achieved through coordination between the agents of the joint cognitive system, and it is viewed as an emergent property of the joint cognitive system rather than as a property of the individual agents. In a recent report on specific joint cognitive systems, involving humans and AI systems, the importance of shared situational awareness in human-AI teams is stressed [5].

Chatzimichailidou [6] defined risk situational awareness as the individual SA of a system agent which refers to the presence of threats and vulnerabilities that may lead to system accidents. Risk distributed situational awareness is considered as a special case of distributed situational awareness, indicating that each agent, on the one hand, may have a detailed picture of the threats and vulnerabilities of the part that the agent controls, but on the other hand only retains a partial overview of the threats and vulnerabilities that are present in the entire system.

Mental models are primary means in situational assessment processes, wherein they guide attention processes and classifying information in perception (level 1 SA), they are a means for integrating the elements towards an understanding of the current situation (level 2 SA), and they are a means to reason about future states (level 3 SA). Mental models were defined by Rouse and Morris [7] as "mechanisms whereby humans generate description of system purpose and form, explanation of system functioning and observed system states, and prediction of future system states" and this definition is well in line with their role in situational assessment. Mental models are personal, internal representations of external reality that people use to interact with the world around them. They are simplified representations of reality and their aspects are influenced by personal goals and motives as well as by the cultural context. In the context of risk perception, it is considered that people use mental models or scripts to reason about hazards ("anything that could lead to harm") [8]. Such mental models describe the components of a hazard, explain how a hazard may change over time, indicate who may be affected by the hazard, and explain how the hazard may be controlled.

2.1.2 Risk awareness concepts

As a key component of the situational awareness of (technical/human) agents in an operational context, the agent should be aware of disturbances that impact the operation that the agent is working in, of the way that these disturbances may evolve, of the impact of these disturbances on the operations, and of the strategies that can be applied such that the effects of the disturbances are kept within acceptable bounds. Such disturbances can be any conditions, events or variations that may affect the operational performance, e.g. poor weather, high workload, failures of technical systems, or large traffic load. Part of such disturbances may have a negative effect on the safety of operations; these are named "hazards".

In choosing strategies to deal with disturbances, agents have to trade off the implications on different performance areas and on short-term and long-term goals. While safety is a key performance area, agents have to deal with the full operational complexity, and decisions impacting safety can only be understood well in relation with other objectives, e.g. completing an operation within a time frame, with acceptable costs, and with limited environmental impact. In decision-making, agents have to deal with uncertainty, since the recognition of disturbances, the way that disturbances may evolve and have impact on the operations, and the effects of strategies are typically only known to a limited extent. The processes for recognizing and interpreting disturbances, and for choosing suitable strategies by individuals are based on their mental models.

Reasoning about safety is often done using the concept of risk, which combines the severity of potential consequences of a particular situation with the likelihood of attaining those consequences. Consequences considered in safety include incidents and accidents, which typically have (very) low likelihood values. The risk concept can also be used for reasoning about key performance areas other than safety, e.g. risk of financial loss, risk of continuity of operations, risk of environmental impact. Also in such areas, severity and likelihood levels can be defined, which are specific for the area considered.

Risk awareness is part of the situational awareness of an agent and it refers to the understanding of the risks in the current work situation, notably including safety risks, and to the decisions made by the agents for strategies for dealing with the perceived risks. A risk mental model is a part of the mental model of an agent and it describes disturbances, ways to recognize disturbances, ways that disturbances can affect particular performance areas, strategies for effectively dealing with disturbances, and ways to decide on appropriate strategies. In classic human information processing terminology, risk awareness refers to the working memory, describing risks that a person sees and understands now and in the near future, whereas a risk mental model refers to long term memory or knowledge base about risks. For example, a pilot might express his risk mental model by arguing that he would initiate a missed approach in case of an unstable approach configuration, so as to assure operational safety. The actual performance of the pilot in an unstable approach condition might be different, because he does not fully recognize the risk as the actual situation evolves and he is already having a delay.

Risk awareness can be updated by interaction processes (e.g. observation, communication, handling) with other humans, technical systems and other entities in the working context, as well as by reasoning processes using risk mental models. Risk mental models can be adapted via the situational awareness of an individual by various learning processes, such as learning risks by own operational experiences, learning risks by communication with colleagues ("story telling"), or institutional learning about risks (e.g. training, pamphlets).

2.1.3 Agent-based modelling

An agent-oriented perspective is useful to conceptualise processes in complex sociotechnical systems. Agent-based modelling considers a sociotechnical system to be composed of several agents and the overall system behaviour emerges from the individual agent processes and their interactions (Figure 3). This provides a highly modular and transparent way of structuring a model, thus supporting systematic analysis, both conceptually and computationally. Agents in a sociotechnical system contain boundaries separating internal states and processes from states and processes external to the agent (in other agents / environment). Relations between an agent's internal and external states or processes are represented strictly via the inputs and outputs of the agent considered. This makes it easier to specify models of complex systems that consist of many interacting entities, thereby facilitating effective study of the emergent behaviour of such systems.

Agents in operations can express a large variety of behavioural patterns and these are influenced by specific processes and characteristics of the agent considered. Especially for human agents there is a wide range of cognitive and affective aspects that influence their behaviour. Such agent-related aspects can be represented by model constructs for each agent (Figure 3). To represent a broad spectrum of such aspects, a library of model constructs is needed [9]. Many of these model constructs are dedicated to human agents and concern aspects like attention, confusion, trust, task scheduling, cognitive control mode, operator functional state, decision making, and task execution.

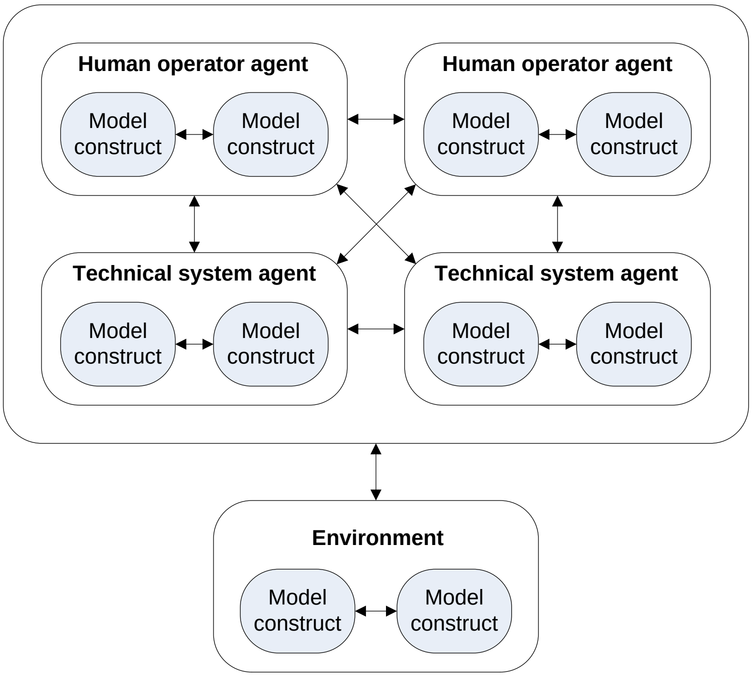

Figure 3. Generic overview of a multi-agent system consisting of human operators and technical systems in an environment. For each agent a number of model constructs is used to represent relevant aspects [9].

2.2 Multi-agent situational awareness modelling

2.2.1 Situational awareness components

The multi-agent situational awareness model construct describes the situational awareness of each agent (human operator, technical system) in a multi-agent system as time-dependent information of other agents, including identity, continuous state variables, mode variables and intent variables [10, 11]. We consider a multi-agent system where agents $k = 1,\dots,n$ have states $s_{t,k}$ at time t:

$$s_{t,k} = \begin{pmatrix} i_{t,k} \\ x_{t,k} \\ \theta_{t,k} \end{pmatrix} \tag{1}$$

where

- $i_{t,k}$ represents the identity of the agent, e.g. a unique name;
- $x_{t,k}$ represents continuous-valued state components of the agent, e.g. position and velocity;
- $\theta_{t,k}$ represents modes of an agent, e.g. a flight phase of an aircraft.

The agents reside in an environment with state $s_{t,0} = \left(\text{Env}, x_{t,0}, \theta_{t,0}\right)$, describing states and modes of the environment, e.g. locations of building, wind speed or being in a rainy condition.

An agent may have situational awareness about each agent in the multi-agent system. The situational awareness of agent *k* at time *t* is denoted as

$$\sigma_{t,k} = \left(\sigma_{t,k}^{1}, \ldots, \sigma_{t,k}^{j}, \ldots, \sigma_{t,k}^{n}\right) \tag{2}$$

The situational awareness of agent *k* about agent *j* at time *t* is a structure that consists of state awareness $\zeta_{t,k}^{j}$ and intent awareness $\upsilon_{t,k}^{j}$:

$$\sigma_{t,k}^{j} = \{\zeta_{t,k}^{j}, \upsilon_{t,k}^{j}\} \tag{3}$$

The state awareness represents estimates held by agent k about current state components of agent j :

$$\zeta_{t,k}^{j} = \begin{pmatrix} \hat{i}_{t,k}^{j} \\ \hat{x}_{t,k}^{j} \\ \hat{\theta}_{t,k}^{j} \end{pmatrix} \tag{4}$$

where

- $\hat{i}_{t,k}^{j}$ denotes the situational awareness by agent *k* at time *t* of the identity of agent *j*, e.g. the situational awareness of a pilot concerning the identity of a nearby aircraft;
- $\hat{x}_{t,k}^{j}$ denotes the situational awareness by agent *k* at time *t* of continuous-valued state components of agent *j*, e.g. the situational awareness by an air traffic controller of the position and velocity of an aircraft;
- $\hat{\theta}_{t,k}^{j}$ denotes the situational awareness by agent *k* at time *t* of discrete-valued state components (modes) of agent *j*, e.g. the situational awareness of an air traffic controller of mode of an alert.

The intent awareness represents expectations by agent k about future states of agent j . It consist of an ordered sequence of components:

$$\upsilon_{t,k}^{j} = \left((\upsilon_{t,k}^{j})_1, \ldots, (\upsilon_{t,k}^{j})_r, \ldots, (\upsilon_{t,k}^{j})_R\right) \tag{5}$$

where $(\upsilon_{t,k}^{j})_r$ is the expectation for states at some future time τ_r (with $\tau_1 < \tau_2 < \ldots < \tau_r < \ldots < \tau_R$) having the following components:

$$(\upsilon_{t,k}^{j})_r = \begin{pmatrix} \bar{\theta}_{t,k}^{j} \\ \bar{x}_{t,k}^{j} \\ \bar{t}_{t,k}^{j} \end{pmatrix}_r \tag{6}$$

where

- $(\bar{\theta}_{t,k}^{j})_r$ denotes a mode of agent *j* that is anticipated by agent *k*;
- $(\bar{x}_{t,k}^{j})_r$ denotes a continuous-valued state component of agent *j* that is anticipated by agent *k*;

- $(\bar{t}_{t,k}^{j})_r$ denotes the expectation of agent *k*, held at time *t*, concerning the time at which the continuous-valued state component $(\bar{x}_{t,k}^{j})_r$ will be attained, or the expectation of the time up to which the mode $(\bar{\theta}_{t,k}^{j})_r$ will be attained by agent j.

For example, in the context of aerodrome manoeuvring, a pilot who intends to subsequently taxi, taxi, line-up and take-off with various speeds and take-off at time $\bar{t}_{\text{take-off}}$ may have the following intent awareness for its aircraft:

$$\upsilon_{t,k}^{j} = \begin{pmatrix} \text{taxi} & \text{taxi} & \text{line-up} & \text{take-off} \\ v_1 & v_2 & v_3 & v_4 \\ \{\cdot\} & \{\cdot\} & \{\cdot\} & \bar{t}_{\text{take-off}} \end{pmatrix},$$

where it is assumed that the pilot does not hold expectations about the time associated with the taxiing and line-up.

2.2.2 Completeness, uncertainty and errors in situational awareness

For safety and resilience of operations proper situational awareness by agents about other agents and the environment are important. Although there is always some uncertainty in the situational awareness of agents and they are not omniscient, the safety of operations should not be affected detrimentally by uncertain, lacking or erroneous situational awareness components. In other words, the performance of the overall multi-agent system should be designed such that it is sufficiently robust for uncertainty and inconsistencies in situational awareness of agents. In support of achieving this, a safety assessment of an operational concept should analyse what uncertainty and inconsistencies in situational awareness may exist and what the impact on the safety of operations can be.

Next we discuss completeness, uncertainty and errors in the components of the situational awareness $\sigma_{t,k}^{j}$ held by agent *k* about an agent *j*.

- The identity $\hat{i}_{t,k}^{j}$ may be unknown or wrong. For instance, an air traffic controller may have mixed the call-signs of two aircraft (wrong identity), or a pilot may not know the call-sign of some nearby aircraft.
- A continuous-valued state $\hat{x}_{t,k}^{j}$ may be unknown or include a particular level of uncertainty. For instance, a pilot may not know the track angle of another aircraft, or a pilot may have a wrong understanding of the rate of descent or the position of the own aircraft. Estimates of continuous-valued states are always wrong to some extent, reflecting the accuracy of a measurement or observation. It is customary to distinguish between estimation errors that are within a normal range and those that are not. The latter then reflects a failure condition.
- A mode $\hat{\theta}_{t,k}^{j}$ may be unknown or wrong. For instance, an air traffic controller does not know flight control settings of an aircraft, or an air traffic controller may think that an aircraft is taxiing while it is actually taking off.
- The intent awareness $\upsilon_{t,k}^{j}$ concerns expectations of future modes and states that will be attained at particular future times. It can be a usual condition that intent awareness components are unknown. For

instance a pilot may not know at what runway another aircraft will be departing from. Since the intent awareness regards the future, its correctness cannot be judged at the current time *t*, but only in retrospect after particular states or modes have been attained. It is relevant for the safety of operations to consider the level of consistency of the intent awareness at a particular time of different agents. For instance, a pilot may intend to take-off from runway *R1* while an air traffic controller intends the aircraft to depart from a different runway.

All components of $\sigma_{t,k}^{j}$ may be unknown, reflecting that agent *k* is completely unaware of agent *j*. In many scenarios part of the components of $\sigma_{t,k}^{j}$ are unknown. This can well be by design of an operation and does not need to pose problems for the safety and effectiveness of operations, but in some cases in may cause safety-critical situations.

2.3 Situational awareness updating processes

In a multi-agent system the agents are updating their awareness in interaction with other agents and the environment. At a high level we can distinguish three types of updating processes (situational assessment) [10, 11], depending on the information transfer between agents:

- Reasoning: process in which the SA of an agent is updated without any interaction with other agents;
- Observation: process in which the SA of an agent is updated via a unidirectional information flow from another agent and or the environment;
- Communication: process in which the SA of an agent is updated via message transfer with another agent, which may lead to unidirectional or bidirectional information flows between the agents.

These processes are described in more detail next.

2.3.1 Reasoning

A situational awareness update process via reasoning is represented by

$$\sigma_{t+\tau,k} = f^{\text{rea}}(\sigma_{t,k}, \varepsilon_{t,k}, \kappa_{t,k}) \quad (7)$$

where τ is the duration of the reasoning process, $\varepsilon_{t,k}$ are stochastic effects, and $\kappa_{t,k}$ is the knowledge base or mental model used for reasoning by agent *k*. During a reasoning process the situational awareness $\sigma_{t,k}^{j}$ of agent *k* can be adapted for multiple agents *j* and for multiple of their components. The duration of the reasoning may vary, for instance depending on the complexity of the task. The stochastic influences $\varepsilon_{t,k}$ represent variability in the reasoning process, leading to differences in situational awareness updates. For example, in a time-constrained situation a human agent could reach different conclusions than in a situation with ample time to reach a conclusion. The knowledge base $\kappa_{t,k}$ represents the rules or associative mappings used by the agent in the reasoning process. The knowledge base is considered to be constant during the situational awareness updating. On a longer term the knowledge base can be adapted (learning).

2.3.2 Observation

A situational awareness update process via observation is represented by

$$\sigma_{t+\tau,k} = f^{\text{obs}}(\sigma_{t,k}, s_t, \varepsilon_{t,k}, \kappa_{t,k}) \quad (8)$$

where τ is the duration of the observation process, s_t are states in the multi-agent system, $\varepsilon_{t,k}$ are stochastic effects, and $\kappa_{t,k}$ is the knowledge base used for observation and interpretation by agent *k*. During an observation process the situational awareness $\sigma_{t,k}^{j}$ of agent *k* can be adapted for multiple agents *j* and for multiple of their components. The duration of the observation may vary, for instance depending on the available means for observation. The stochastic influences $\varepsilon_{t,k}$ represent variability and errors in the observation process. The knowledge base $\kappa_{t,k}$ represents the rules or associative mappings used by the agent for the observation and interpretation of sensor data. The knowledge base is considered to be constant during the situational awareness updating, but may be adapted by learning on a longer term.

2.3.3 Communication

A situational awareness update process via communication is represented by a combination of message send and receive processes

$$\begin{aligned} (m_{t+\tau_s,k_s}, \sigma_{t+\tau_s,k_s}) &= f^{\text{send}}(\sigma_{t,k_s}, \varepsilon_{t,k_s}, \kappa_{t,k_s}) \\ \sigma_{t+\tau_s+\tau_r,k_r} &= f^{\text{rec}}(\sigma_{t+\tau_s,k_r}, m_{t+\tau_s,k_s}, \varepsilon_{t+\tau_s,k_r}, \kappa_{t+\tau_s,k_r}) \end{aligned} \quad (9)$$

where agent k_s is sending a message $m_{t+\tau_s,k_s}$ which is received by agent k_r and leads to an update in the situational awareness of the receiver. The send process is based on the situational awareness and knowledge base of the sender agent, which may be influenced by stochastic influences (e.g. errors), and it has a duration τ_s. It also has impact on the situational awareness of the sending agent, namely the awareness that a message has been sent to another agent. The receive process is based on the message sent, and on the situational awareness and knowledge base of the receiver agent, which may be influenced by stochastic influences (e.g. misinterpretation errors), and it has a duration τ_r. Bidirectional communication entails combinations of send and receive processes.

2.3.4 Situational awareness update scheduling

In addition to impact of the reasoning, observation, and communication processes, the dynamic evolution of situational awareness of agents depends on the scheduling of these processes. This means: at what times are the processes initiated? Situational awareness updating processes are part of the overall task scheduling processes of agents. These determine how often tasks are done, when tasks are done in parallel, when they are done sequentially, and what the priorities of tasks are. The task scheduling is agent-specific and it depends on the situational awareness and knowledge (mental models) of an agent.

2.4 Risk and uncertainty in situational awareness models

Risk awareness concerns the dynamic understanding by an agent of risks that evolve during operations in a multi-agent system. Risks represent combinations of the severity of future unwanted conditions that may arise during operation and the likelihood of these conditions. Risk awareness by an agent thus must represent the agent's understanding of the likelihood of future unwanted conditions. As a basis for this, the situational awareness model is extended by uncertainty awareness, which represents awareness by an agent of uncertainty in state and intent awareness. Next, Section 2.4.1 describes models for uncertainty awareness in state awareness, Section 2.4.2 describes uncertainty awareness in intent awareness, and Section 2.4.3 presents risk awareness models.

2.4.1 Uncertainty awareness in state awareness

As defined in Section 2.2.1, the state awareness includes identity, continuous state variables, and mode variables. For each of these components an agent may be aware of uncertainty.

Uncertainty awareness by agent *k* regarding the identity of agent *j* is represented by a series of N_I possible identities in combination with probability estimates of these identities:

$$\hat{i}_{t,k}^{j} = \begin{pmatrix} \hat{i}_{t,k}^{j,1} & \cdots & \hat{i}_{t,k}^{j,N_I} \\ \hat{p}_{t,k}^{I,j,1} & \cdots & \hat{p}_{t,k}^{I,j,N_I} \end{pmatrix} \tag{10}$$

with $\sum_q \hat{p}_{t,k}^{I,j,q} = 1$. For instance, a pilot may think that the call-sign of some nearby aircraft is likely ($\hat{p}_{t,k}^{I,j,1} = 0.9$) "AC1", but maybe ($\hat{p}_{t,k}^{I,j,2} = 0.1$) "AC2".

Uncertainty awareness by agent *k* regarding a continuous-valued state of agent *j* is represented by lower and upper bounds of a 95% confidence interval:

$$\hat{x}_{t,k}^{j} = \left(\hat{x}_{t,k}^{j,L}, \hat{x}_{t,k}^{j,U}\right) \tag{11}$$

For instance, an altitude measurement system may be aware of the uncertainty range in its measurement, or a bystander may estimate the speed of a drone to be between 30 and 50 km/h.

Uncertainty awareness by agent *k* regarding a mode of agent *j* is represented by a series of N_θ possible modes in combination with probability estimates of these modes:

$$\hat{\theta}_{t,k}^{j} = \begin{pmatrix} \hat{\theta}_{t,k}^{j,1} & \cdots & \hat{\theta}_{t,k}^{j,N_\theta} \\ \hat{p}_{t,k}^{\theta,j,1} & \cdots & \hat{p}_{t,k}^{\theta,j,N_\theta} \end{pmatrix} \tag{12}$$

with $\sum_q \hat{p}_{t,k}^{\theta,j,q} = 1$. For instance, an air traffic controller may doubt whether some an aircraft has initiated a take-off run ($\hat{p}_{t,k}^{\theta,j,1} = 0.5$) or the aircraft is taxiing ($\hat{p}_{t,k}^{\theta,j,2} = 0.5$).

2.4.2 Uncertainty awareness in intent awareness

As defined in Section 2.2.1, the intent awareness is represented by an ordered sequence of expected future states: future modes, future continuous-valued states, and expectations of associated times. For each of these components an agent may be aware of uncertainty.

Uncertainty awareness by agent *k* regarding a future mode $(\bar{\theta}_{t,k}^{j})_r$ is represented by a series of N_θ possible future modes in combination with probability estimates of these future modes:

$$(\bar{\theta}_{t,k}^{j})_r = \begin{pmatrix} \bar{\theta}_{t,k}^{j,1} & \cdots & \bar{\theta}_{t,k}^{j,N_\theta} \\ \hat{p}_{t,k}^{\bar{\theta},j,1} & \cdots & \hat{p}_{t,k}^{\bar{\theta},j,N_\theta} \end{pmatrix}_r \tag{13}$$

For instance, a pilot may expect that a nearby aircraft will likely ($\hat{p}_{t,k}^{\bar{\theta},j,1} = 0.9$) make a right turn, but might ($\hat{p}_{t,k}^{\bar{\theta},j,2} = 0.1$) make a left turn.

Uncertainty awareness by agent *k* regarding a future continuous-valued state $(\bar{x}_{t,k}^{j})_r$ is represented by lower and upper bounds of a 95% confidence interval:

$$(\bar{x}_{t,k}^{j})_r = \left(\bar{x}_{t,k}^{j,L}, \bar{x}_{t,k}^{j,U}\right)_r \tag{14}$$

For instance, an air traffic controller expects that an aircraft will be taxiing with a speed between 25 and 35 km/h.

Uncertainty awareness by agent *k* regarding the expected time $(\bar{t}_{t,k}^{j})_r$ for attaining future mode or state value is represented by lower and upper bounds of a 95% confidence interval:

$$(\bar{t}_{t,k}^{j})_r = \left(\bar{t}_{t,k}^{j,L}, \bar{t}_{t,k}^{j,U}\right)_r \tag{15}$$

For instance, an air traffic controller may expect that an aircraft will initiate a take-off run within a particular time range, or a driver may expect that a car will have reached a speed of 100 km/h within 8 to 12 seconds.

2.4.3 Risk awareness

Risk awareness by an agent represent the agent's understanding of the likelihood of future unwanted conditions during operations. Risk awareness by agent *k* at time *t* about risks of agent *i* is represented by a number of risks $\left(\rho_{t,k}^{j}\right)_r$:

$$\left(\rho_{t,k}^{j}\right)_r = \begin{pmatrix} \beta_{t,k}^{j} \\ \eta_{t,k}^{j} \\ p_{t,k}^{j} \\ \alpha_{t,k}^{j} \\ I_{t,k}^{j} \end{pmatrix}_r \tag{16}$$

where

- $\left(\beta^{j}_{t,k}\right)_r$ denotes a type of risk, e.g. collision with aircraft, collision with object, collision with human, collision with terrain, empty battery. It may also represent risks that are not safety-related, e.g. the risk that passengers in an aircraft loose connecting flights, or the risk that a package is not delivered in time;
- $\left(\eta^{j}_{t,k}\right)_r$ denotes one or more severity classes of the possible future condition, e.g. Catastrophic, Major, Minor, Negligible;
- $\left(p^{j}_{t,k}\right)_r$ denotes probability estimates of the severity classes of the possible future condition, which can be a value or a probability class, e.g. Almost Certain, Likely, Moderate, Unlikely;
- $\left(\alpha^{j}_{t,k}\right)_r$ denotes the acceptability of the risk, e.g. Acceptable, Marginal, Unacceptable;
- $\left(I^{j}_{t,k}\right)_r$ denotes a set of identities of agents that are involved in the risky situation, e.g. another aircraft that poses a collision risk. The set is empty if there are no other agents involved in the particular risky condition.

The risk awareness $\rho^{j}_{t,k}$ is added as a component to the situational awareness $\sigma^{j}_{t,k}$. The risk awareness by agent *k* may be empty for many agents *j*. For instance, a drone pilot may only be concerned about the risks of the drone that he/she is controlling. The multitude of agents for which an agent holds non-empty risk awareness depends on the responsibilities of the agent in the operation. For instance, an air traffic controller is responsible for a set of aircraft in a sector and needs to maintain situational awareness for all these aircraft.

Risk awareness is updated by a reasoning process as in Eq.(7), which may follow earlier or quasi-simultaneous observation or communication processes. The knowledge base $\kappa_{t,k}$ for reasoning about risks represents knowledge by an agent about interpretation of risk in the operation. This knowledge base may for instance be formed by rules or mappings, stemming from training or experiences.

2.5 Awareness-based acting and control by an agent

The extended situational awareness (including risk awareness) forms the basis for acting and control actions by an agent to maintain the operation in a safe and efficient manner. The first step is decision-making by an agent what kind of control actions are needed to achieve this. In the situational awareness modelling framework such decision-making can be represented by extending the intent awareness construct. In particular, the intent awareness $\upsilon^{j}_{t,k}$, which includes modes, continuous states and associated times of agent *j* that are anticipated by agent *k*, is extended by changed modes, continuous states, and associated times that are expected by agent *k* following control actions to reduce risks to acceptable levels. The intent awareness of Eq.(5) is extended as follows:

$$(\upsilon_{t,k}^{j})_r = \begin{pmatrix} \bar{\theta}_{t,k}^{j} & \bar{\theta}_{t,k}^{j,c} \\ \bar{x}_{t,k}^{j} & \bar{x}_{t,k}^{j,c} \\ \bar{t}_{t,k}^{j} & \bar{t}_{t,k}^{j,c} \end{pmatrix}_r \tag{17}$$

where

- $(\bar{\theta}_{t,k}^{j,c})_r$ denotes a mode of agent *j* that is expected by agent *k* following a control action, e.g. it is expected by an air traffic controller that an aircraft will change its flight phase from approach to missed approach after an instruction by the controller to go around (to avoid a conflict on the runway);
- $(\bar{x}_{t,k}^{j,c})_r$ denotes a continuous-valued state component of agent *j* that is expected by agent *k* following a control action, e.g. it is expected by a drone pilot that a drone will change its course following a command by the drone pilot in the control station (to avoid a conflict with another drone);
- $(\bar{t}_{t,k}^{j,c})_r$ denotes the expectation of agent *k*, held at time *t*, concerning the time at which the continuous-valued state component $(\bar{x}_{t,k}^{j})_r$ will be attained, or the expectation of the time up to which the mode $(\bar{\theta}_{t,k}^{j})_r$ will be attained by agent *j* following a control action, e.g. the time that a instructed course by an aircraft has been achieved following an instruction by an air traffic controller.

As discussed in Section 2.2.2 there exists uncertainty in the intent awareness components. This also applies to the additional components. For instance, the drone pilot wanting to let the drone change course may not be able to achieve this, if there would be a (temporary) failure of the command and control link to the drone. Also an agent may have uncertainty awareness about the additional situational awareness components. For instance, a drone pilot may know that a command and control link is not very stable in a particular urban environment.

In a similar way, the risk awareness of Eq.(16) can be extended by components that represent the expected risk following a control action:

$$\left(\rho_{t,k}^{j}\right)_r = \begin{pmatrix} \beta_{t,k}^{j} & \beta_{t,k}^{j,c} \\ \eta_{t,k}^{j} & \eta_{t,k}^{j,c} \\ p_{t,k}^{j} & p_{t,k}^{j,c} \\ \alpha_{t,k}^{j} & \alpha_{t,k}^{j,c} \\ I_{t,k}^{j} & I_{t,k}^{j,c} \end{pmatrix}_r \tag{18}$$

For instance it could be that agent *k* expects that probability of a severity class of some future condition is decreased due to a control action, such that the risk is changed from being unacceptable to acceptable.

The update of the extended situational awareness, including the intent following control actions can be represented by a reasoning process of the agent as in Eq.(7). In this case the applied knowledge base $\kappa_{t,k}$ includes rules, heuristics, mappings or some optimization process for conflict resolution. In the context of risk awareness, conflict resolution means that the agent expects that the control actions imply that the risks are reduced as much as possible to acceptable levels.

Following an update of the situational awareness with adapted intent awareness, the associated control actions must be effectuated. For many interactions between agents this may be represented by the communication process of Eq.(9), where a message is sent by one agent and received and interpreted by another agent. This can for instance represent the sending of a voice instruction by an air traffic controller to a pilot to change course, or the presentation of a resolution advisory by an airborne collision avoidance system to a pilot, transmission of a control action by a drone pilot to the flight control system of a drone.

The communication process of Eq.(9) leads to an update of the situational awareness of an agent. In addition we need an acting process that has impact on the physical state $s_{t,k}$ of an agent, as defined in Eq.(1). The acting process is represented by:

$$\begin{aligned} &(m_{t+\tau_s,k_s}, \sigma_{t+\tau_s,k_s}) = f^{\text{send}}(\sigma_{t,k_s}, \varepsilon_{t,k_s}, \kappa_{t,k_s}) \\ &\dot{s}_{t,k_r} = f^{\text{phys}}(s_{t,k_r}, m_{t+\tau_s,k_s}, \lambda_{t,k_r}) \text{ for } t \geq \tau_s + \tau_r \end{aligned} \tag{19}$$

where a particular control setting $m_{t+\tau_s}$ is transmitted by a sender agent k_s to a receiver agent k_r . Next, for times exceeding the times for sending and receiving/processing of the control setting, the dynamics of agent k_r governed by control settings λ_{t,k_r} are changed such that it comes in another regime. For instance, an aircraft may start to climb or to make a turn due to an action by a pilot or a flight control system, or a car may start to decrease its speed due to a braking action by a driver or an automated system.

2.6 Integrated overview of the situational awareness components and processes

An integrated overview of the situational awareness components and processes presented above in Sections 2.2 to 2.5 is shown for two interacting agents in the diagram of Figure 4. Agents can be human operators or technical systems and they reside in an environment as described in Section 2.2.1. Agents have physical states, representing their identity, continuous-valued states like position, speed, body movement, and discrete modes like the flight phase of an aircraft. Agents have situational awareness about the agents and environmental states in the multi-agent system. The main situational awareness components are the state awareness (Section 2.2.1), the intent awareness (Section 2.2.1), uncertainty awareness for states and intents (Sections 2.4.1 and 2.4.2), and risk awareness (Section 2.4.3). The situational awareness updating (or situational assessment) processes are reasoning, observation and communication (Section 2.3). Each of these processes use the knowledge base of the agent. Furthermore, reasoning processes are only based on the agent's situational awareness, observation processes are also based on observed physical states, and communication processes are based on message transfer. Such message transfer is also used to communicate changes in control settings of a physical system thus leading to awareness-based acting and control by the agent, e.g. for a human to walk to a position, or a flight control system to attain a particular flight level (Section 2.5). Finally, as indicated in Figure 4, the knowledge base of an agent can be adapted by learning processes based on the situational awareness of the agent.

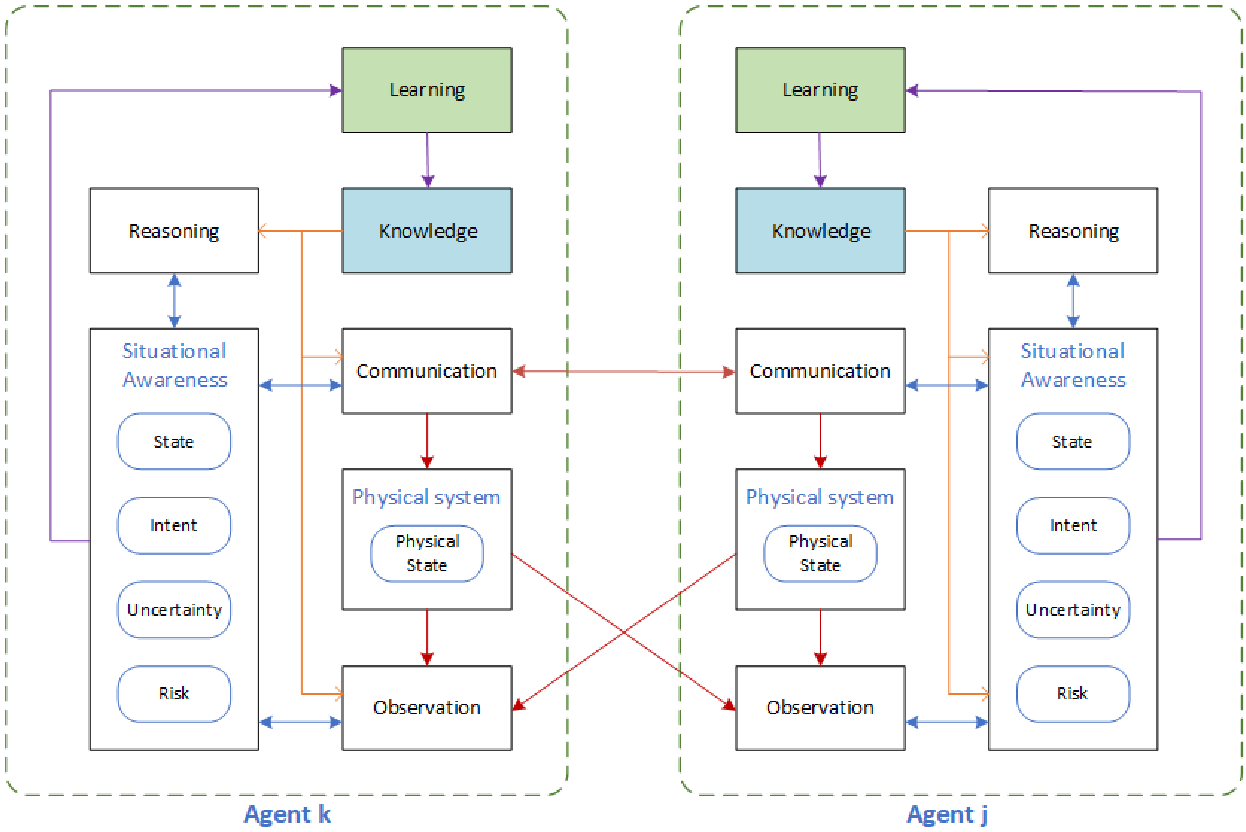

Figure 4. Integrated overview of situation awareness components and processes for two interacting agents

3 Concepts and DAA systems for low-level drone operations: state-of-the-art

This chapter provides a concise review of state-of-the-art for concepts of low-altitude UAS operations (Section 3.1) and for detect and avoid systems for UAS operations (Section 3.2).

3.1 Concepts for low-altitude UAS operations

3.1.1 FAA UTM ConOps

The Federal Aviation Administration (FAA) of the USA published a concept of operations (ConOps) for UTM [12]. It presents a vision and associated operational and technical requirements for development of an UTM ecosystem for low altitude airspace, focusing on UTM operations below 400 ft above ground level (AGL) and including beyond visual line of sight (BVLOS) operations.

A diagram of the key participants, services and supporting infrastructure in the UTM ConOps is shown in Figure 5.

- UAS operators are persons or entities responsible for the overall management of UAS operations.
- The remote pilot in command (RPIC) is the person responsible for the safe conduct of each UAS flight. The RPIC adheres to operational rules of the airspace in which the unmanned aircraft (UA) is flying; avoids other aircraft, terrain and obstacles; assesses and respects airspace constraints and flight restrictions; and avoids incompatible weather/environments.
- Public safety entities can access UTM operations data as a means to ensure safety of the airspace and persons and property on the ground, security of airports and critical infrastructure, and privacy of the general public. The general public can access data that is required to be publicly available.
- FAA's primary role is to provide a regulatory and operational framework for operations and to provide FAA-originated airspace constraint data to airspace users.
- A UAS service provider (USS) is an entity that assists UAS Operators with meeting UTM operational requirements that enable safe and efficient use of airspace. USS services support operations planning, intent sharing, strategic and tactical de-confliction, conformance monitoring, remote identification, Airspace Authorization, airspace management functions, and management of off-nominal situations.
- The USS Network shares operational intent data, airspace constraint information, and other relevant details across the network to ensure shared situational awareness for UTM participants.
- UAS Supplemental Data Service Providers are sources for access to terrain and obstacle data, specialized weather data, surveillance, and constraint information.
- Flight Information Management System enables exchange of airspace constraint data between the FAA and the USS Network, as well as other FAA data.

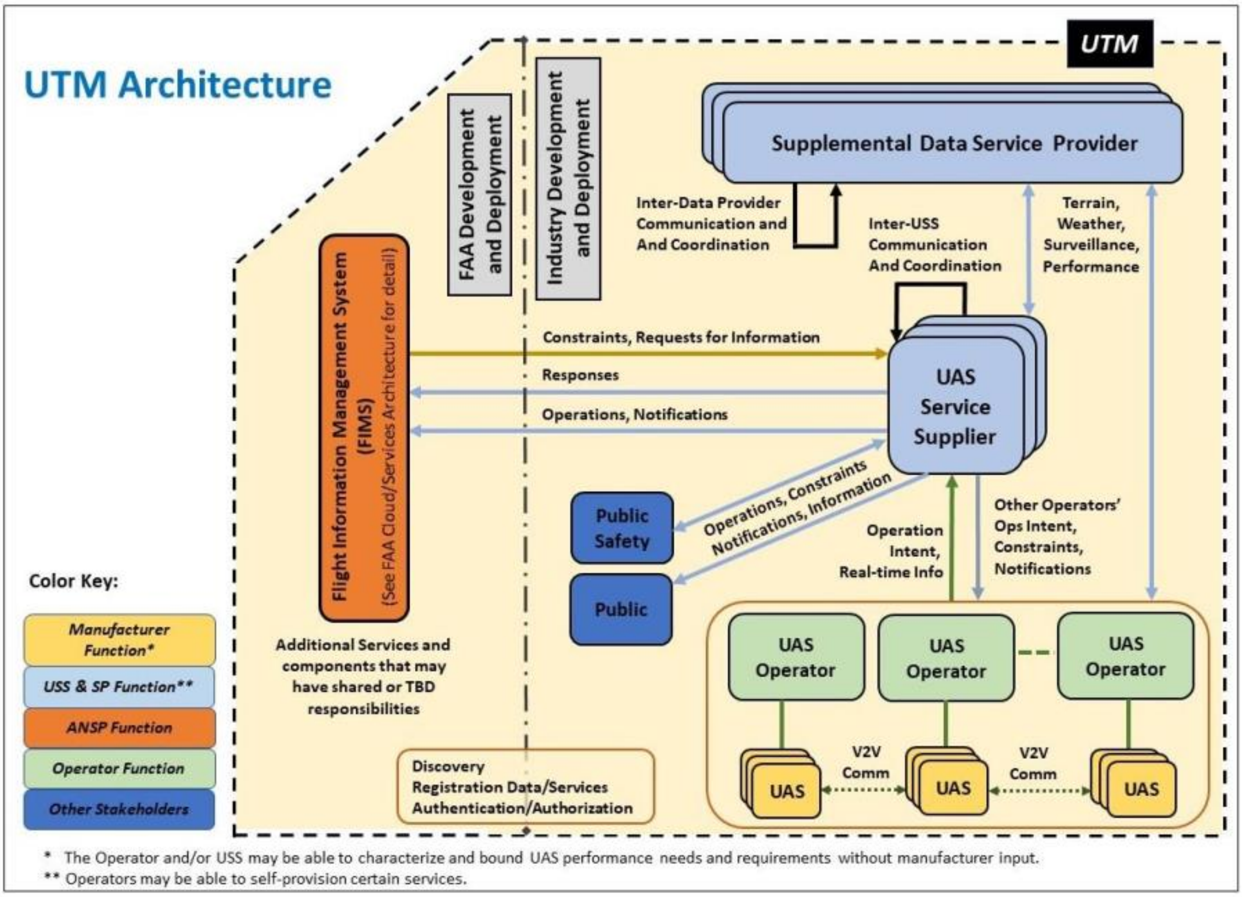

Figure 5. Architecture of the FAA UTM ConOps [12]

Operation planning

With UTM, flight intent is submitted and shared among operators for situational awareness in the form of an Operation Plan. The Operation Plan is developed prior to the operation and indicates the four-dimensional (4D) volume of airspace within which the operation is expected to occur, the times and locations of the key events associated with the operation, including launch, recovery, and any other information deemed important (e.g., segmentation of the operation trajectory by time). While a single volume can be used, segmentation of that 4D volume promotes the efficient use of the airspace and reduces the likelihood of overlapping operations.

Constraint information

UAS Operators are responsible for identifying unexpected operational conditions or flight hazards that may affect their operation. This information is collected and assessed both prior to and during the operation in order to ensure the safe conduct of the operation. USSs may support this Operator responsibility by supplying airspace constraint and advisory information, weather, and other relevant data. Near real-time advisories are provided through the USS Network, and are made available to affected users regarding:

- Traffic (e.g., aircraft known and unknown to the USS Network, non-conforming flights)
- Weather and winds (e.g., unexpected wind gusts or storm)

- Other hazards pertinent to low altitude flight (e.g., unexpected obstacles such as a crane or power-line Notice to Airmen [NOTAM], bird activity, local UAS restrictions, and other UAS specific hazard information).

Separation
UAS Operators are ultimately responsible for maintaining separation from other aircraft, airspace, weather, terrain, and hazards, and avoiding unsafe conditions throughout an operation. Separation is achieved via shared intent, shared awareness, strategic deconfliction of airspace volumes, vehicle tracking and conformance monitoring, technologies supporting tactical deconfliction, and the establishment of procedural rules of the road (e.g., right-of-way rules). The Operator is responsible for in-flight coordination with other Operators, and can utilize services of a USS to facilitate this coordination. The Operator's Performance Authorization may require onboard communications, navigation, and detect and avoid (DAA) equipment to maintain separation tactically.

Operational scenarios
Several illustrative operational scenarios are presented in [12]. Operators conduct commercial and recreation operations in rural, suburban, and urban environments. Commercial operations include inspections (e.g., infrastructure, agricultural), scenic photography/videography, medical operations (e.g., organ transport), and package delivery. UTM stakeholders work together to foster shared situational awareness, develop and disseminate notifications to UAS Operators about airspace changes, and support safe UA interactions with manned and unmanned aircraft.

3.1.2 EUROCAE OSED for DAA in VLL operations

An operational services and environment definition (OSED) for detect and avoid in very low-level (VLL) operations by UAS [13] has been published by EUROCAE, a European organization for aviation standards.

Very-low level operations in this OSED are below minimum altitude for flights under visual flight rules, which imply up to 1000 ft above building tops in urban environments and up to 500 ft above ground and obstacles out of urban areas.

The OSED considers remotely piloted operations, where the remote pilot (RP) may be in the loop or on the loop, supported by automation up to Level of Automation 6 (computer makes decisions, but gives human option to veto prior to implementation). A remote pilot may control multiple UAS operations simultaneously.

A number of types of VLL operations are described for precision agriculture (e.g. multispectral imagery, crop dusting/spraying), inspection missions (e.g. bridges, power lines, rail), mapping surveying and aerial imaging, aerial firefighting, delivery of goods (e.g. intra urban, inter urban, rural, high value cargo), and air taxi operations.

A number of hazards and situations to be avoided are described in [13]. They concern insufficient separation of a UA with another UA not capable of carrying passengers, with another UA capable of carrying passengers, with manned aircraft, with terrain (e.g. mountains, ridges, valleys, water), with obstacles (e.g. masts, bridges, cranes, wires, ground vehicles), with meteorological and atmospheric phenomena (e.g. clouds, wind, smoke, turbulence), with groups of people, and with flying wildlife (e.g. birds, bats, swarms of insects). The means of detection for these cases include cooperative communication, non-cooperative sensing, terrain and obstacle maps and databases, and weather information services.

Proposed separation minima for the hazards considered are listed in Table 1. They are subject matter experts' insights that can be adapted in follow-up studies.

In support of assuring sufficient separation the DAA function supports the remote pilot in the following ways:

- Provision of information to maintain proper situational awareness regarding air traffic, terrain, obstacles, weather, groups of people, and flying wildlife.
- Provision of remain well clear (RWC) advisories for each of the hazards described, allowing the RP to initiate a RWC manoeuvre for assuring separation. Depending on the environment the RP may be required to communicate with ATC and/or interact with VLL air traffic management services prior to implementing a RWC manoeuvre.
- Provision of collision avoidance (CA) advisories for all hazards, except for meteorological and atmospheric phenomena. The CA function shall automatically initiate a CA manoeuvre when appropriate, but allows the RP to override proposed or automatically initiated CA manoeuvres.

Table 1. Proposed separation minima of an unmanned aircraft flying at VLL with another entity [13]

Hazard	Remain well clear minimum Horizontal / Vertical	Collision avoidance minima Horizontal / Vertical
UA not capable of carrying passengers	70 m / 50 m	35 m / 25 m
UA capable of carrying passengers	700 m / 80 m	350 m / 40 m
Manned aircraft	700 m / 80 m	350 m / 40 m
Terrain	30 – 50 m / 30 – 50 m	15 – 25 m / 15 – 25 m
Obstacle	30 – 50 m / 30 – 50 m	15 – 25 m / 15 – 25 m
Weather	600 m / NA	NA
Groups of people	30 – 50 m / 30 – 50 m	15 – 25 m / 15 – 25 m
Animals (incl. flying wildlife)	30 – 50 m / 30 – 50 m	15 – 25 m / 15 – 25 m

3.1.3 SESAR U-space concept of operations

The SESAR Joint Undertaking is an institutionalised European partnership between private and public sector partners for research and innovation in ATM. As part of the EU Aviation Strategy and SESAR, U-space is a set of new services and specific procedures designed to support safe, efficient and secure access to airspace for large numbers of drones [14]. In the SESAR CORUS-XUAM project a ConOps for U-space is developed, which meets the needs of urban air mobility (UAM), including both goods and passenger air transport un urban areas [15].

A high-level overview of stakeholders in the U-space architecture with a focus on UAM is shown in Figure 6. It includes UAS operators, UAM operators, UAS manufacturers, U-space Service Providers, Common

Information Service Providers (ensuring quality, integrity, accuracy, and security of information), Supplemental Data Service Providers (e.g. weather data, ground risk data), Communication, Navigation and Surveillance (CNS) Service Providers, Air Traffic Service providers, Aeronautical Information Service Provider, Aerodrome operator, Vertiport operator, Competent Authority, Authority for safety and security and Emergency Responders (police, fire brigade, search and rescue), UAS delivery client, UAM passenger, Airspace user, and general public.

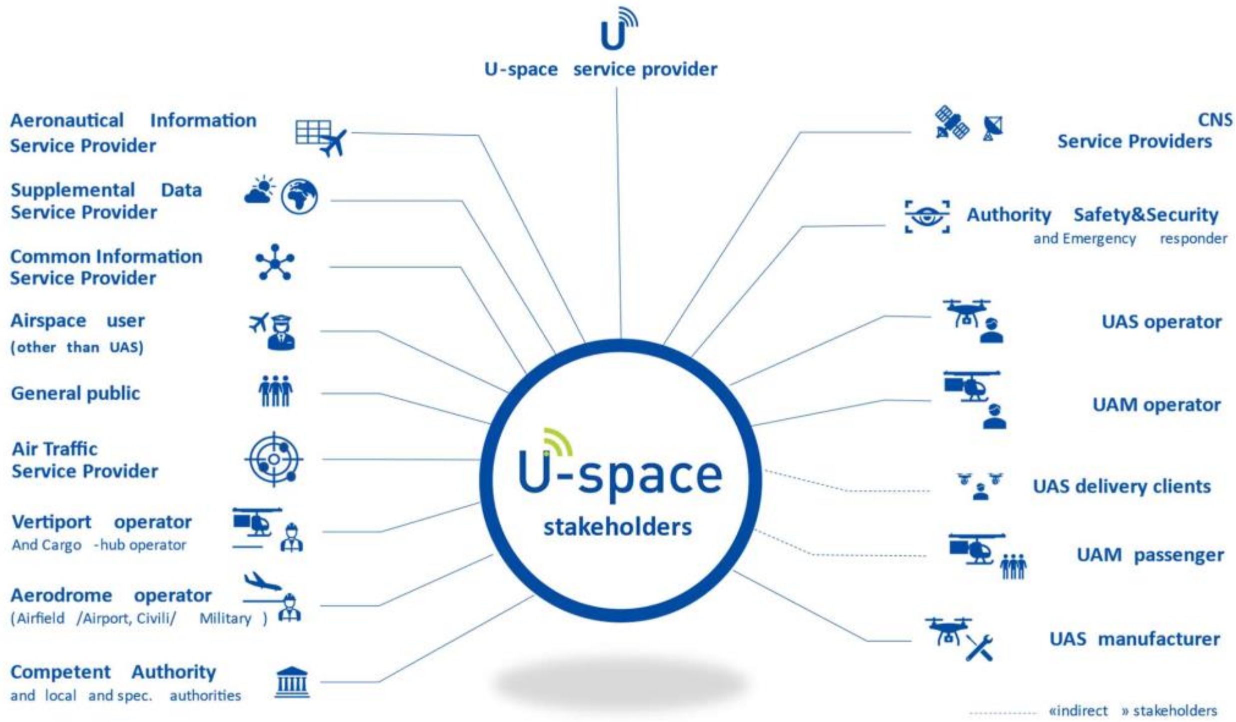

Figure 6. U-Space stakeholders with focus on urban air mobility [15]

A large number of U-space services are defined at a high level in [15], including registration, network identification, tracking, surveillance data exchange, drone aeronautical information management, geo-awareness, strategic conflict prediction and resolution, dynamic capacity management, tactical conflict detection and resolution, traffic information, infrastructure monitoring, etc. Examples are given how these services can be provided for specific mission types, including architectural photography, aerial mapping, power line inspection, pharmaceutical delivery, and an air taxi. Demonstrations of SESAR U-space studies which address elements of the operational concept in more detail are introduced in [16].

3.2 Detect and avoid systems for UAS operations

3.2.1 Taxonomy for conflict detection and resolution

A review of conflict resolution methods for manned and unmanned aviation in [17] provides a taxonomy for conflict detection and conflict resolution categories. Herein, conflict detection discerns the following categories:

- **Surveillance.** Aircraft surveillance regards information of key states as position, altitude, and identity of aircraft in an airspace. The aircraft surveillance can be *centralised dependent*, where surveillance information is transferred via a central agent, such as air traffic control on the ground, *distributed dependent*, where surveillance information is actively shared between nearby aircraft via a datalink, or *independent*, where aircraft use on-board non-cooperative sensors to detect other aircraft and other obstacles.
- **Trajectory propagation.** Conflict detection can be based on *state-based* future trajectories, which extend aircraft's current position and velocity vectors, or on *intent-based* future trajectories, which includes future waypoints in an aircraft's flight plan.
- **Predictability assumption.** The detection of a conflict is based on predicted future positions of nearby aircraft. Uncertainty in such prediction can be handled in various ways: *nominal*, meaning that uncertainties in trajectory propagation are not considered, *worst-case*, using the largest possible trajectory changes stemming from uncertainties, or *probabilistic*, using a maximum-likelihood estimate for future trajectories.

The conflict resolution categories in [17] are the following:

- **Control.** The control of separations can be *centralised*, where decisions on conflict resolution and future trajectories are made in a central location for multiple aircraft (e.g. in an ATC centre), or it can be *distributed*, where each aircraft is responsible for its own conflict avoidance.
- **Method.** The type of method for conflict resolution in a centralised control approach can be *exact*, which finds a global optimum for a conflict situation, or *heuristic*, which attempts to yield a good, but not necessarily optimum solution in a reasonable time. The type of method for conflict resolution in a distributed control approach can be *prescribed*, where predefined right-of-way rules are used (e.g. traffic from the left must give way), *reactive*, where avoidance manoeuvres are based on the conflict geometry, or *explicitly negotiated*, where a conflict resolution employs explicit communication between the involved aircraft.
- **Multi-actor conflict resolution.** The type of method for conflict resolution in a centralised multi-actor conflict ($n>2$) can be *sequential*, which optimize trajectories one by one according to prioritization of aircraft, or *concurrent*, where all trajectories are computed simultaneously. For conflict resolution in a distributed multi-actor conflict, the resolution approach can be *pairwise sequential*, where each manoeuvre resolves a conflict with one intruder, starting with the highest-priority conflict, *pairwise summed*, where resolution vectors resulting from each pairwise resolution are summed, or *joint solution*, where multiple intruders are considered simultaneously and a single solution is found that simultaneously resolves all conflicts that the ownship is involved in.
- **Avoidance planning.** The type of avoidance planning can be defined by the look-ahead time with respect to the conflict: *strategic* regards a long-range action, hours to about 20 minutes before the closest point, *tactical* regards mid-range actions, up to about 3 to 5 minutes before the closest point of approach, and *escape* regards short-term manoeuvres.
- **Avoidance manoeuvre.** The type of avoidance manoeuvre can include *heading variation*, *speed variation*, or *vertical variation*. Furthermore, *flight plan* modifications can adapt multiple future waypoints of an aircraft.
- **Obstacle types.** A conflict detection and resolution method may prevent collision with *static* obstacles, with *dynamic* obstacles, or with *all* obstacles.
- **Optimization.** The optimization approach applied in the conflict detection and resolution may take into account the impact on *flight time*, on *flight path*, or on *fuel/energy consumption*.

In [17] an overview of methods is provided for conflict detection and resolution methods for manned and unmanned aviation according to this taxonomy.

3.2.2 ACAS X programme

The ACAS X programme is FAA sponsored R&D towards a more advanced ACAS [18, 19]. Arguments for its development include increased flexibility for future operations, increased adaptability for new surveillance inputs, reduced collision risk and less nuisance alerts, and collision avoidance capabilities for general aviation and unmanned aircraft systems (UAS) [19]. ACAS X has a system architecture that uses logic tables, which have been optimized for specific aircraft operations in particular airspaces. Changes in operations, aircraft types and airspaces can be accommodated by off-line optimization of the logic tables. The modular architecture of ACAS X allows for effective use of multiple surveillance sources, including transponder-based, Automatic Dependent Surveillance - Broadcast (ADS-B), and others.

The ACAS X architecture is composed of a Surveillance and Tracking Module (STM), which correlates surveillance data from multiple sensors for the track estimation of an intruder, and a Threat Resolution Module (TRM), which uses estimated tracks and other state data from the STM as an input for determining a potential threat. If any intruder poses a threat, the time to loss of well clear or near mid-air collision (NMAC) is predicted and an optimal action is chosen based on a look-up table with precomputed strategies. Various ACAS X variants have been developed or are under development:

- ACAS Xa/Xo uses active interrogation of intruders and it is intended as a successor of TCAS II for large commercial operations [20]. It provides traffic advisories (TAs) and resolution advisories (RAs) for vertical manoeuvres.
- ACAS Xu is designed for large UAS and it provides Remain Well Clear (RWC) functionality in addition to a Collision Avoidance functionality [21, 22]. It is able to use non-cooperative surveillance inputs, such as air-to-air radar in its STM. It makes use of alerting and guidance in the horizontal plane as well as the vertical plane, and these are provided independently.
- ACAS sXu is designed for smaller UAS with a wingspan of 25 feet or less and height of 12 feet or less, which are expected to operate mostly below 1200 ft AGL [23, 24]. The STM uses surveillance data to maintain tracks of nearby aircraft as well as terrain/obstacles. The TRM uses decoupled vertical and horizontal components. All sXu guidance is directive, allowing for auto-response. The nominal response delay for auto-response to RAs is less than 1 s, independent from the type of RA. The protection volume for sUAS intruders is based on 50 ft horizontal and ±15 ft vertical volume, which is called sUAS Near Mid-Air Collision (sNMAC) [25]. Towards manned and large UAS intruders the sXu logic applies a RWC volume of 2000 ft horizontally and ±250 ft vertically. Selection of a protection volume based on intruder type is called dynamic scaling.
- ACAS Xr is being developed for rotorcraft operations, including air taxis.

The basis of ACAS X systems are probabilistic estimations of ownship and othership states, which are combined with optimized decision logic tables to achieve advised actions. The optimized decision logic tables have been determined off-line using a partially observable Markov decision process (POMDP) model and dynamic programming [26, 27]. This optimization process uses (1) probabilistic dynamic models for pilot response and aircraft movements, (2) a reward function with an extensive set of cost components for close proximities and types of advisories, and (3) dynamic programming to maximize the reward function, leading to state-action values that are stored in large look-up tables.

Given a perfect model of the environment as a finite Markov decision process (MDP), dynamic programming is guaranteed to lead to an optimal policy for the finite states in the environment. This is a deterministic policy, which maximizes the reward function. Dynamic programming can be seen as reinforcement learning for completely known environments. Reinforcement learning is an artificial intelligence (AI) approach where a machine learns what to do so as to maximize a reward signal in an (typically not completely known) environment [28]. Some practical considerations in applying dynamic programming to airborne collision avoidance systems are the following.

- There is no finite state space, but agents moving in time-space continuums, which must be approximated using discretization, requiring large numbers of discretized states.
- Not all states are observable and POMDP models of pilot response and aircraft movements are used, which are representations of reality (including epistemic uncertainty).
- It is not known beforehand what a suitable reward function is. ACAS development involves an iterative process where the operational and safety impact of attained ACAS performance is evaluated, leading to adaptation of parameters in the reward function [29].
- The RWC functionality (as in ACAS Xu) needs to account for longer time horizons than the CA functionality, implying more uncertainty in aircraft state predictions and larger state-space discretization tables.
- The logics of vertical and horizontal advisories (as in ACAS Xu) are obtained independently, such that they do not need to be optimal in combination (blended manoeuvres).

3.2.3 DAIDALUS

DAIDALUS (Detect and Avoid Alerting Logic for Unmanned Systems) is a DAA reference system of the RTCA MOPS for DAA [30] developed by NASA. These MOPS regard DAA systems that assist remote pilots of larger UAS; they do not apply to small UAS operating in low-level environments. The software implementation has been verified against the formal models and validated against multiple stressing cases jointly developed by the US Air Force Research Laboratory, MIT Lincoln Laboratory, and NASA [31].

Two aircraft are considered to be well clear of each other, if appropriate distance and time variables determined by the relative aircraft states remain outside a set of predefined threshold values. These distance and time variables are closely related to variables used in the Resolution Advisory (RA) logic of the Traffic Alert and Collision Avoidance System Version II (TCAS II). DAIDALUS core logic is based on ownship-centric, state-less algorithms (see Figure 7) that

- Determine the current pairwise well-clear status between ownship and traffic aircraft (Detection Logic)
- Compute maneuver guidance for the ownship to maintain or regain well- clear status (Maneuver Guidance Logic)
- Determine pairwise alert level between ownship and traffic aircraft (Alerting Logic)

DAIDALUS software is available at https://nasa.github.io/daidalus/ under NASA's Open Source Agreement. The interface provides access to a large number of parameters to tune the performance.

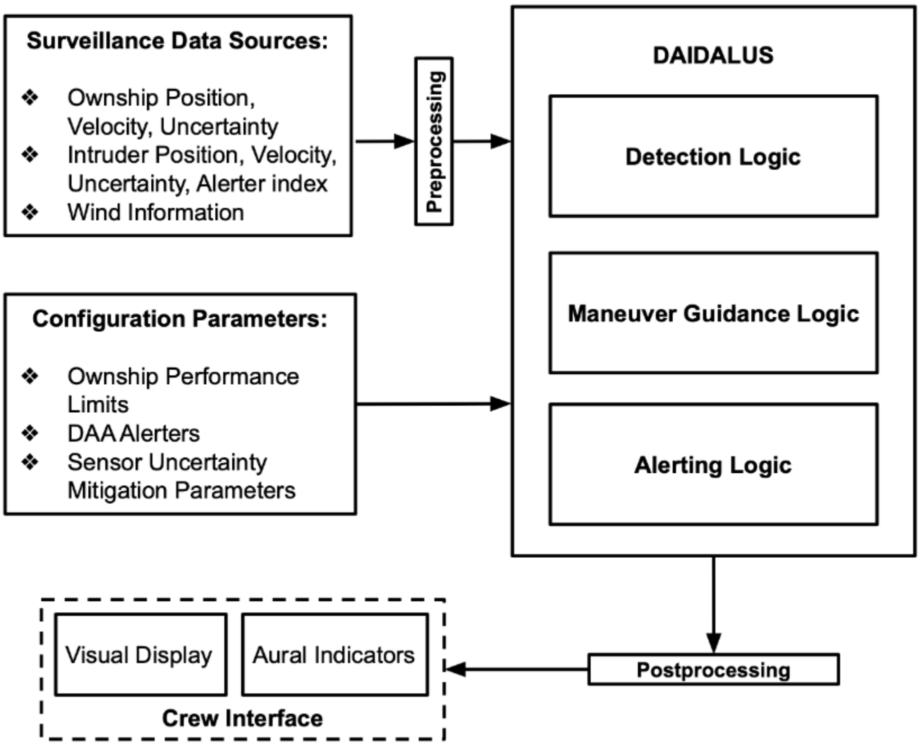

Figure 7. High-level architecture of DAIDALUS library

The alerting logic of DAIDALUS is rule-based, in contrast to the use of optimized look-up tables in ACAS Xu. Another key difference with ACAS Xu is that DAIDALUS has been designed for the Remain Well Clear functionality and does not include a collision avoidance functionality. A comparison of early versions of ACAS Xu and DAIDALUS is presented in [32]. Using tuned parameters DAIDALUS was applied in a simulation study for a UAM use case, showing an effective reduction in close proximity risk [33].

4 Awareness-based UTM concept

This chapter provides the high-level definition of an awareness-based concept for UAS traffic management. A motivation of the concept is provided in Section 4.1, the environment and types of operations in the concept are described in Section 4.2, the state and intent awareness components of the agents are provided in Section 4.3, the risk awareness elements of the agents are indicated in Section 4.4, and approaches for awareness-based acting and control are provided in Section 4.5.

4.1 Motivation

As follows from the review in Section 3, the development of a safe and efficient traffic management system for UAS operations in urban environments is a demanding and current topic in aviation. It is explicitly indicated in the UTM ConOps of FAA [12] that shared situational awareness and shared intent are important means for assuring sufficient separation between aircraft. The ways to achieve such shared situational awareness and shared intent are still a part of research and development.

Existing and developing ACAS and DAA systems are based only on current absolute or relative state estimates (position, velocity) of involved aircraft; this applies to TCAS II, ACAS Xa, ACAS Xu, ACAS sXu, ACAS Xr, DAIDALUS. This means that future (intended) positions, as considered in a flight plan, are not used as means to remain well clear or for collision avoidance. Also RWC advisories are not shared or coordinated between DAA systems, which restricts attaining shared situational awareness about these manoeuvres. These limitations may have repercussions on the effectiveness of assuring separation and on the efficiency of the advisories with respect to flight time and energy consumption.

Furthermore, current designs of prevalent DAA systems are mostly focused on conflicts with other aircraft and may include some ground obstacles. They do not take explicitly into account other risks, such as collisions with humans, birds or an empty battery.

So the SymAware framework for shared situational awareness and risk awareness are in line with general concepts of operations for UTM and they may help to overcome limitations of current DAA systems.

4.2 Environment and types of operation

The concept considers operations at low altitudes in an urban environment. The urban environment includes high buildings, moving cranes, birds, humans, and cars. There can be strong winds, which can be locally amplified by buildings. There can be bad weather in the urban environment.

The following types of operations are foreseen in the urban environment:

- Surveillance operations by small UAS. These are drones flying in a pattern over a limited area. In an urban environment the surveyed areas are likely to be inhabited, such that are safety risks with respect to people and objects on the ground if the operations are not maintained at sufficient distance, or if operations become uncontrollable. In addition there could be other problems, like privacy violations and noise hindrance.
- Delivery operations by small UAS. These are drones flying from a limited number of distribution centres to a large number of places in the urban environment, and vice versa. In addition to the general risks posed during the en-route part of the operations, there may be particular risks to nearby people during the delivery phase of the operation.
- Air taxi operations. These support urban air mobility for transport of people between a limited number of air taxi hubs in the urban area. Obviously a main potential risk is that to passengers during the flight.

It is assumed that nominal operations of the small UAS as well as the air taxis are operated autonomously, without human operators in the loop of the operation. As such, the operations can be performed completely automatically by the flight management systems of the aircraft, based on available information, flight planning, and detect and avoid systems. There may be human operators on the loop of the operations, who maintain oversight of the safety and efficiency of the operations, and who may intervene in the case of problems.

It is assumed that the aircraft have high-speed access to a UTM information provider (e.g. via a 5G telecommunication network). Furthermore, the aircraft have high-speed vehicle-to-vehicle communication links with nearby aircraft. These can be used to share data on state and intent awareness, e.g. regarding position, speed, future waypoints. It is assumed that the aircraft have radar and/or visual observation systems that allow them to detect nearby other aircraft, buildings, objects, flocks of birds, and humans. All aircraft have battery supplied electric motors.

4.3 Situational awareness of agents

The generic multi-agent situational awareness model of Section 2.2 discerns between various components for state and intent awareness. In the UTM concept the flight management systems and DAA systems of the aircraft can include the following state awareness components:

- position and speed of own aircraft;
- positions and speeds of nearby aircraft;
- flight modes of own and nearby aircraft (e.g. take-off, landing, en-route);
- positions and heights of buildings;
- observed moving objects;
- observed nearby humans;
- observed flock of birds;
- current weather condition;
- battery state.

The intent awareness of the agents can include the following components:

- next waypoints of the intended flight, including the destination;
- next flight phases and associated speeds;

- planned manoeuvres following DAA advisories.

Additional state and intent awareness components may be added during the detailed model development.

The generic updating processes for state and intent awareness of Section 2.3 discern between reasoning, observation, and communication. In the UTM concept with autonomous UASs, the reasoning processes regard the interpretations and decisions made by the FMS and DAA systems. The observation processes regards radar and vision systems that are used to update the situational awareness. The communication processes regard the sharing of information by the vehicle-to-vehicle communication links and the connection with the UTM information provider. Various cases of shared situational awareness and their impact on the overall performance of the multi-agent system will be evaluated in the study.

4.4 Risk awareness

Risk awareness of UASs concerns the dynamic understanding by the flight management systems and detect and avoid systems of risks that evolve during their operations (see also Section 2.4). The risk awareness encompasses the following risks:

- risk of collision with nearby aircraft;
- risk of collision with a fixed object or building;
- risk of collision with a moving object;
- risk of collision with a bird;
- risk of collision with a human on the ground;
- risk of strong local winds;
- risk of encountering bad weather;
- risk of attaining an empty battery.

The risk awareness regarding these risks is based on the state and intent awareness components regarding associated aircraft or environmental entities, and on associated uncertainty awareness. The prime component of the detailed modelling will be the development of models for the knowledge base for risk awareness based on the available information of agents. Various cases of risk awareness models and their impact on the overall performance of the multi-agent system will be evaluated in the study.

4.5 Awareness-based acting and control

As explained in Section 2.5 the extended situational awareness (including risk awareness) forms the basis for acting and control actions by an agent to maintain the operation in a safe and efficient manner. At a high level two basic approaches for the development of such awareness-based control system can be distinguished: (1) rule-based acting and control, (2) optimization/learning-based acting and control.

A rule-based system for acting and control uses a set of rules to decide on actions by an agent based on the state and intent awareness and the risk awareness. To maintain sufficient separation with other aircraft and thus to reduce the risk of a collision to acceptable levels, existing state-based algorithms will be used as a basis, e.g. the rules incorporated in DAIDALUS (see also Section 3.2.3). These rules will be extended to account for intent awareness components, such as next waypoints or destination, and planned DAA manoeuvres by other aircraft. Incorporation of such planned waypoints and the coordination that can be attained by shared DAA manoeuvring intents are expected to improve the effectiveness of the acting and control. In addition, the awareness of other risks will be incorporated in the knowledge model rules to modify or weight various options. For instance, if the risk of attaining an empty battery is becoming more severe, the manoeuvring may be tuned to a trajectory that is shorter, but closer to other aircraft.

An optimization/learning-based system for acting and control uses an optimization/learning approach to configure a control system that provides actions, based on extended situational awareness. The dynamic programming approach applied in the ACAS X programme (see Section 3.2.2) is an optimization approach. A disadvantage is that the required discretization of the state space leads to very large tables, such that it is not quite amenable to addition of various situational awareness components. As dynamic programming is a type of reinforcement learning, a more promising approach could consist of a neural network as control system which is optimized by reinforcement learning. The inputs of such neural network can consist of state and intent awareness components and risk awareness elements. The outputs of the neural network represent manoeuvring actions. The cost function driving the learning process would minimize the expected risk, based on training of a large set of encounter-scenarios.

5 Conclusions and follow-up

The objective of SymAware is to develop a framework for awareness in multi-agent systems that is compatible with the internal models and specifications of robotic agents and that enables safe simultaneous operation of collaborating autonomous agents and humans. The objectives of the aviation and automotive use cases in WP5 are to implement and validate the SymAware framework, and thus to demonstrate its usefulness in practical and demanding use cases.

As a basis for the use case development the initial conceptualization of situational and risk awareness of D1.1 [1] has been extended in Section 2. It provides high-level, generic mathematical models for state and intent awareness in a multi-agent sociotechnical system, situational assessment processes, inclusion of uncertainty and risk awareness by agents, and awareness-based acting and control by agents, describing adapted intents to be achieved by agents in efforts to reduce risks to acceptable levels.

As follows from the review in Section 3, the development of a safe and efficient traffic management system for UAS operations in urban environments is a demanding and current topic in aviation. This development is well aligned with the situational awareness framework supporting increasingly autonomous systems of SymAware. It is explicitly indicated in the UTM ConOps of FAA [12] that shared situational awareness and shared intent are important means for assuring sufficient separation between aircraft. However, existing and developing ACAS and DAA systems are based only on current absolute or relative state estimates (position, velocity) of involved aircraft, and they do not consider future (intended) positions. This affects the effectiveness of assuring separation and on the efficiency of the advisories with respect to flight time and energy consumption.

So the SymAware framework for shared situational awareness and risk awareness are in line with general concepts of operations for UTM and they may help to overcome limitations of current DAA systems. A high-level concept for autonomous operations in an urban environment, including surveillance and delivery operations by small UAS, and air taxi operations has been defined in Section 4. It provides descriptions of the types of situational awareness and risk awareness components of the autonomous UAS, as well as rule-based and optimization/learning-based approaches for acting and control actions by these agents.

Next in Task 5.1.2 detailed models will be developed for the situational awareness, risk awareness, and awareness-based acting and control of the UAS operations. These will form the basis for simulations of the autonomous UAS operations in Task 5.1.3, where the impact of various conditions of situational awareness, risk awareness, and awareness-based acting and control will be evaluated. This will lead to new designs and recommendations for DAA systems in UTM.

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