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The Proposal of a Concept of Artificial Situational Awareness in ATC

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Abstract

Automation is one of the most promising solutions to the airspace capacity problem. However, we believe that in order to safely implement advanced automation concepts in air traffic control, it is necessary for AI and humans to share situational awareness. One of the main objectives of this concept proposal is to explore the effects and possibilities of distributed human-machine situational awareness in en-route air traffic control operations. Instead of automating isolated individual tasks, such as conflict detection or coordination, we propose to create a basis for automation by developing an intelligent situation-aware system. The sharing of the same situational awareness between the members of the air traffic controller team and AI enables the automated system to reach the same conclusions as air traffic controllers when faced with the same problem and to be able to explain the reasons for these conclusions. Machine learning can be used to predict, estimate and filter at the level of individual probabilistic events, an area in which it has shown great ability so far, whereas the reasoning engine can be used to represent knowledge and draw conclusions based on all the available data and explain the reasons for these conclusions. In this way, the artificial situational awareness system will pave the way for future advanced automation based on machine learning. Here, we will explore which technologies and concepts are useful in building the artificial situational awareness system and propose the methodology for testing the AI situational awareness.

Keywords: *Air traffic control, artificial intelligence, situational awareness, concept proposal*

1. Introduction

The air traffic controller's job will be very different in the future; it will have to be adapted to new circumstances.

The growth in air traffic in Europe is already putting a strain on the European air traffic management system. In 2018, delays in en-route air traffic management (ATFM) increased by 104%, while traffic increased by only 3.8% in the same period. As in previous years, the main cause of ATFM delays on routes was the lack of air traffic control (ATC) capacity (34%) [1]. The current air traffic throughput for a given sector is constrained by air traffic controller (ATCO) workload. The growing number of aircraft means that the workload of air traffic controllers is increasing to such an extent that it is possible for the ATCO to lose situational awareness (SA), leading to unsafe operations. Demand capacity balancing (DCB) measures are then employed to reduce the workload of individual ATCOs and ATFM delay is thus created.

Automation is one of the most promising solutions to the capacity problem, but it is clearly stated in the SESAR

Single Programming document for 2019-2021 that the human should be kept in the loop in order to ensure safety:

> *Automation could provide the key to significant performance improvements across many aspects of ATM. On the other hand, human cognitive abilities, especially in safety-critical situations, can have positive benefits and provide strong arguments against full autonomy in certain situations. The challenge is therefore to propose solutions with automation levels or autonomy that have the capability to provide substantial and verifiable performance benefits whilst fully addressing safety [2].*

Therefore, we believe that to implement advanced automation concepts it is required that the artificial intelligence (AI) and human are able to share the SA. Exploring the effects and possibilities of distributed human-machine situational awareness in en-route operations is one of the main objectives of the methodology presented here. Instead of automating isolated individual tasks, such as conflict detection or coordination, we propose to create a basis for automation by developing an intelligent situation-aware system. Sharing the same team situational awareness (TSA) between ATCO team members and AI (Figure 1) will allow the automated system to reach the same conclusions as ATCOs when confronted with the same problem and explain the reasoning behind those conclusions.

Previous research has shown that SA will actually improve in systems with greater automation as long as it was applied to information acquisition and action implementation, as compared to automation of cognitive functions, specifically information analysis [3]. This means that automation will provide the greatest benefit if it replaces monitoring tasks instead of automating the higher-level decision tasks.

Other studies have shown that automation can be beneficial to maintaining the situational awareness, even at intermediate levels of automation [3,4]. On the other hand, it was found that monitoring automation involves considerable workload [5,6], therefore, self-monitoring automation with graceful degradation characteristics should be employed to the greatest degree possible.

ATCOs work in teams and they share a common SA, often called team SA (TSA). Automation tools are mostly focused on supporting the individual ATCO whereas many of the air traffic control (ATC) functions are a team effort [7,8]. Higher cognitive functions, such as managing team task load or anticipating team member's reactions and capabilities, are very difficult to automate [7]. For this reason, automation must be able to share the same TSA as the rest of the team.

In previous SESAR Exploratory Research project BEST, ATM-specific ontology was developed for data handling in support of SWIM [9]. Guidelines (aimed at practitioners) were developed on how ontologies can be used flexibly to describe metadata and how they can be used in innovative yet scalable ways. We are trying to integrate ideas and conclusions of the BEST project with advances in AI and ML in order to allow AI to partake in team situational awareness. The ontologies developed in BEST will be used as a basis for development of knowledge graphs (KG) used by the reasoning engine.

In other industries, ontologies were used in combination with reasoning engines to achieve a level of situational awareness, e.g. in SAPPHIRE (Situational Awareness and Preparedness for Public Health Incidences and Reasoning Engines) project [10], which shows that reasoning engines using domain-specific ontologies are able to participate in TSA.

Operators, such as ATCOs, working in environment with high level of automation show signs of out-of-the-loop (OOTL) effect [11–13]. SESAR Exploratory Research (ER) project MINIMA has shown that OOTL effect can be mitigated by varying the level of automation [14]. To mitigate the problem, SESAR ER project AUTOPACE proposes improvement in training with emphasis on preparing ATCOs for potential system failures and for recovering control [15]. While these mitigation measures might bear fruit, it is inevitable that OOTL effect will always be present at higher levels of automation which makes TSA even more important.

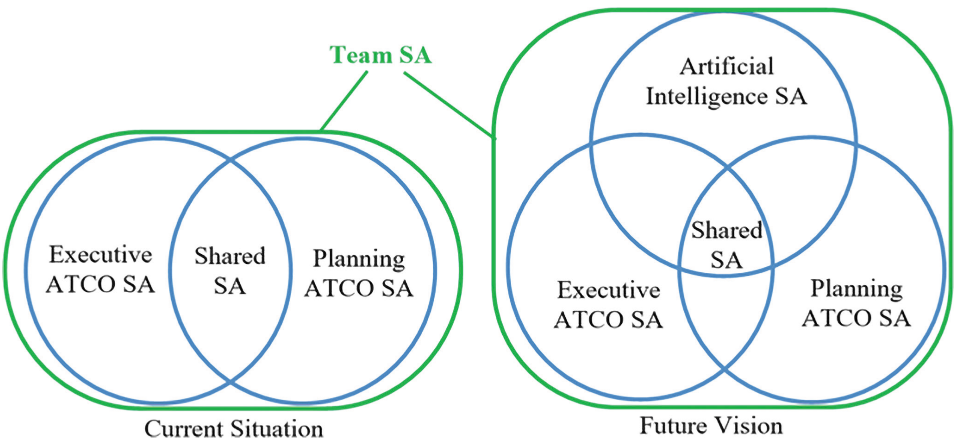

Fig. 1. Concept of Distributed Situational Awareness for Future Automated Systems

2. Vision of AI Situational Awareness

Researchers from different fields have for some time realized that a sense of "awareness" of many systems' own situation is an enabler for robust and dependable behavior even when undergoing radical changes in the environment and drastically diminished capabilities. This insight has recently led to a proliferation of work on self-awareness and other system properties such as self-organization, self-configuration, self-optimization, self-protection, self-healing, etc., which are sometimes subsumed under the term "self-*" [16].

Achieving low-level situational awareness is trivial, any PID controller for example can be considered to have some sort of situational awareness (Level 1 in framework proposed by [16]). However, to achieve higher levels of SA, the system needs to make meaningful observations, make robust semantic interpretation and meaningful attribution, it needs to have an appropriate reaction and be aware of its own goals and history thereof. Semantic web approach (ontologies + rules) to achieving situational awareness is not a novel idea, it has been attempted in different forms and in different fields. In [17], the authors propose a "Situation Awareness Assistant (SAWA) based on Semantic Web technologies that facilitates the development of user-defined domain knowledge in the form of formal ontologies and rule sets and then permits the application of the domain knowledge to the monitoring of relevant relations as they occur in situations". Artificial situation awareness was explored in a narrow scope in embedded systems for healthcare [18], and in a much wider scope in the defence industry for battlefield management [19]. This type of broader situational awareness comes closest to the function of the system as we propose it, which can be found in the literature.

On the other hand, semantic webs and knowledge engineering in general have been present in the field of ATM for some time. The authors in [20]an approach for runtime analysis and automated knowledge-based IT management is presented and applied to the example of an Air Traffic Control (ATC propose an approach for knowledge-based IT management of air traffic control systems which combines the strengths of formal ontologies and Complex Event Processing. Further application of knowledge graphs, semantic web, and ontologies in ATM can be found in [21–24]. None of these, however, address the application of such technologies for achieving artificial situational awareness or ensuring transparency of the machine-learning systems.

In current ATC operations each human team member, executive or planner ATCO, is aware of:

- traffic situation (by looking at the radar screen),
- their own state (e.g. feeling rested or tired),
- other team member state (by verbal/non-verbal communication), and
- system state (by inspecting the error messages, warning lights etc).

On the other hand, the system is unaware of the state of the ATCOs, it is unaware of the traffic situation, and it has very limited awareness of its own state.

Our vision for the future automation concept of en-route ATC operations includes human-machine distributed team SA (TSA) with sector team consisting of executive ATCO, planning ATCO, and AI (actors). Actors will be able to continually monitor each-other states, with AI being aware of the probable human actors' states via analysis of traffic situation. Tasks will be allocated dynamically according to actor states, including graceful degradation of automation ensuring business continuity. According to current task analysis [25], the following monitoring tasks could be automated just by introducing the AI SA into the TSA:

- Monitoring incoming traffic and projecting future flight states.
- Identifying, analysing, and solving entry/transit/exit problems, including climbs/descents, with ability to explain solution to ATCO in natural or coded language on request; warn of unsolved problems.
- Requesting information from, and providing it to, aircraft; maintaining up to date intent information for each aircraft.
- Monitoring conformance of aircraft to planned trajectory.
- Identifying conflicts, detecting ATCO's actions related to conflict solving, and monitoring evolution of conflict solution; alert if solution applied by ATCO does not lead to conflict resolution and explain the reasoning.
- Identifying opportunities for improvement of quality of service.
- Monitoring adverse weather areas and restricted airspace; projecting their evolution.

Also, this system could be an automated proxy between the sector team and the supervisors by including team state reporting, sector state reporting, alerting, and coordination on traffic de-complexing.

Assumptions and key enabling technologies for successful development of such a system are:

- TSA must represent the complete situation with all interactions among aircraft, humans and systems, including accurate representation of system and human states.
- Essential component of TSA is the ability to project future states from current ones.
- A single actor (machine or human) does not have to have complete SA; in this way SA is only partial for each actor.
- Individual SA should overlap to the extent that makes the operations safe and practicable.
- TSA should be distributed among actors in a way that favours individual strengths.
- Data sources and communication infrastructure, including datalink, are available.

3. AI Situational Awareness Methodology Concept

Our approach combines reasoning engine employing predicate logic (first-order logic) based on an ATC knowledge graph system (including rule-based reasoning) with a machine learning (ML) approach for prediction and estimation. ML will be used at a lower level to predict individual probabilistic events (e.g. estimated time over waypoint) whereas the reasoning engine is used at a higher level to draw conclusions from the system state. By combining the reasoning engine with ML, we believe that it will be possible for AI to be 'aware' of the situation in a manner similar to a human, that is, AI will be able to assess complex interactions between objects, draw conclusions, explain the reasoning behind those conclusions, and predict future system states.

To enable exploration of the effect of human-machine distributed situational awareness a framework for ATC-specific knowledge representation (i.e. a domain-specific knowledge graph system) should first be developed. In this context knowledge graph should not be considered just as another form of data encoding but, by representing all relevant object attributes, rules, relations, axioms etc. in ATC domain, as a basis for inferring new knowledge and drawing conclusions about the state of the system, both at the level of individual components and at the global level. While ATM-specific ontologies have been used for data encoding and translation in recent years, our approach to automation, combining ML with knowledge graph system (including the rule-based reasoning engine) for AI situational awareness is completely novel.

To feed the data into the knowledge graph, a set of translators from aeronautical data standards to Resource Description Framework (RDF) format will be developed or reused from previous projects (e.g. BEST project in SESAR ER). Other attributes, relations, rules and axioms will be encoded to RDF in cooperation with ATCO experts.

Reasoning can be done by automatic inference, which is a process for filling the gaps in the ontology, or by running a query to answer a specific question. Queries will be developed in cooperation with ATCO experts for each of the monitoring tasks to be automated. By performing these queries at short intervals, continuous monitoring will be achieved. Running queries over large stores of triples can be time consuming, so optimization techniques will be employed to reduce the number of triples, and hardware will be adapted for the purpose (large memory and multiple cores).

4. Concept Assessment

To assess the concept, it will be necessary to determine whether the developed system possesses a quality comparable to human situational awareness. Certainly, artificial SA will not be nearly as comprehensive as human, but we expect that reaching partial SA will be enough to prove the feasibility of the concept. The baseline for a comparison will first have to be developed by assessing ATCO's SA in a set of given air traffic situations.

Human SA

There are several SA assessment tools, which have been developed over the years. According to [17] the measures can be grouped into three categories:

a) query techniques, in which the subjects are asked directly about their perception of certain aspects of the situation: Situation Awareness Global Assessment Technique (SAGAT), Situation Present Assessment Method (SPAM), Situation Awareness bei Fluglotsen der Langstreckenkontrolle im Kontext von Automatisierung (SALSA), Situation Awareness Probe S (SPAPS),

b) rating techniques, in which either the subjects themselves or observers of the subjects are asked to rate SA along a number of dimensions, typically presented in a series of scales: Situation Awareness Rating Technique (SART), Cranfield Situation Awareness Scale (C-SAS), Situation Awareness Linked Indicators Adapted to Novel Tasks (SALIANT), Situation Awareness Behaviorally Anchored Rating Scale (SA/BARS), and

c) performance-based techniques, in which the level of SA is inferred from the level of performance. The rationale underlying this technique is that a good SA is needed to achieve good performance. This might be the use of objective measurement tools techniques like eye tracking.

Taking into account the previous existing SA measurement tools, [17] two specific kinds of measurement tools have been developed to assess ATCO`s SA in Air Traffic Management (ATM):

1) SA for Shape on-Line (SASHA_L), which is a query technique based on existing measure, especially SPAM. The new component of this SA assessment tool is that the queries are formulated by a subject matter expert (SME) in real-time, taking into account the real scenario as it unfolds. Thus, the SME asks a question if he/she decides that it is appropriate to do so.

2) SA for SHAPE Questionnaire (SASHA_Q) – a questionnaire technique using carefully chosen questions that focus on key elements of SA which controllers have identified themselves. The SASHA_Q is a post-exercise self-rating technique. It consists of ten questions that were especially designed by taking into account the views of controllers themselves about SA and its indicators. Both measures are primarily concerned with controllers` SA when using computer-assistance tools and other forms of automation support.

By assessing SA in ATCO's it seems reasonable and useful to use different kinds of measurement tools as proposed by [17]. The use of SASHA_L and SASHA-Q in combination with an objective measurement tool like eye tracking (to assess perception modes) seems appropriate when studying SA in the mentioned context of the herein proposed research.

Artificial SA

To assess the artificial SA, we formulate our framework according to Jantsch and Tammemäe [16]. We shall define the system aware of certain characteristics of the environment, if three conditions are met:

1. The data interpretation is meaningful;
2. The drawn conclusions are robust; and
3. The reaction of the system is appropriate. [16]

Based on these three rules, we can define five conditions for being aware of the environment and two conditions for being aware of itself. For property P we define the following conditions related to the awareness of the said property by the system [16]:

I. The system performs physical measurements or observations based on the received measurement that are used to derive the values of P by means of a meaningful semantic interpretation.

II. The semantic interpretation is robust.

III. There is a semantic attribution which is meaningful.

IV. The system's reaction to its perception of P is appropriate.

V. A history of the evolution of the property over time is maintained, in particular of the increasing or decreasing deviations over time.

As mentioned previously, we also define two conditions for being aware of itself [16]:

A. The system can assess how well it meets all its goals, thus it has an understanding which goals should be achieved and to which extent they are achieved.

B. The system can assess how well the goals are achieved over time and when its performance improves or deteriorates.

The assessment of the SA level can be performed by writing SPARQL queries designed to elicit the same information as that requested by the ATCO in SASHA_L/Q. These queries will be focused on analyzing the traffic situation in en-route ATC. Additional queries will be designed to elicit information about other members of the team. The purpose of these queries will be to determine whether the system can gain insights into the extent of team SA and the state of other actors. Overall, this methodology and the concept itself were only applied when so many questions remained unanswered.

This framework enables us now to define six levels of SA, Table 1.

SA Level	Description
0	A functional system instinctively reacts to a given input always in the same manner; its output is a mathematical function of its input. If it also fulfills the conditions I – IV, we define it to be at Level 0.
1	An adaptive subject tries to minimize the difference between input values and corresponding reference values. If it also meets conditions I – IV it is aware at level 1.
2	A self-aware system 1. is aware of at least one system property and one environment property according to conditions I – IV and condition A, 2. it contains an inspection engine that periodically derives one integrated attribution of the system, and 3. it computes its actions based on (a) the monitored and attributed properties of the system and of the environment; (b) the attributed expectations on the system and on the environment; (c) the set of goals set for the system and the environment.
3	A history sensitive self-aware system fulfills all requirements of Level 2 and, in addition, fulfills the history conditions V and B (thus satisfying all seven conditions).
4	A predictive system is a history sensitive self-aware system of Level 3 and, in addition, its decision-making process involves a simulation engine that can simulate the effects of actions on the environment and on the system, thereby predicting future states and behaviors of both the system and its environment.
5	In addition to self-awareness, group awareness means that the system distinguishes between itself, the environment and the peer group. The latter is treated differently by associating it with peer group specific expectations and goals.

5. Conclusion

We have presented here a concept for the development of the artificial situational awareness system in ATC based on combining machine learning modules and reasoning over knowledge graphs. The expected benefits of such a system are the ability to integrate and cross-check other sources of information, detect erroneous information, and automate some of the monitoring tasks.

The remaining research questions are numerous.To what extent are human and artificial SA even comparable? What is the maximum level of SA that can be obtained with KGs and/or reasoning engines? Does the complexity of knowledge engineering make benefits of artificial SA system irrelevant? How feasible is it to encode all required semantics for ATC en-route operations? Is first-order logic powerful enough for all types of queries that will be needed? Is it safe to include AI situational awareness in conjunction with ATCOs in TSA?

In our future work we hope to answer these questions and to find out whether the concept of artificial situational awareness is feasible in air traffic control.

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