SCI-341 Symposium on
Situation Awareness of Swarms and Autonomous Systems
Technical Evaluation Report

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1.0 INTRODUCTION

The SCI (Systems Concepts and Integration) Technical Panel aims to gain knowledge to assure successful and cost-effective NATO missions in the future. The primary objective of the SCI-341 Symposium was "to enable experts to assess the state of the art of the concept and practice of Situation Awareness (SA) for Swarms and autonomous systems" [1]. Swarms of autonomous systems (e.g., UxVs) are expected to play an important role in modern warfare. Situation awareness "(…) denotes the up-to-the-minute (current) relevant information (and recognition of that information) about the surrounding environment that is important to move about, operate equipment or maintain a system" [1]. For successful use of swarms of autonomous systems, situation awareness has to be assured for both human operators and autonomous systems.

To achieve the Symposium's purpose, the agenda includes three topics, which are addressed in one session each: Situation awareness and autonomy, Humans as Systems in the Loop, and Swarm Intelligence and Situation Awareness. The three session were complemented by two Keynotes and a Discussion. The SCI Symposium was hosted by the Estonian Ministry of Defense. It was conducted as a virtual event on 18.-19. May 2021. Of 140 registered participants, approximately 70 participated (from GBR, EST, USA, TUR, ITA, DEU, DNK, SWE, PRT).

The present technical evaluation report summarizes the main statements and conclusions of the presented papers. Hence, it does not contain the author's own opinion or ideas, but only summarizes those papers or cites relevant parts. In the following, situation awareness is abbreviated as SA, autonomous system as AS.

2.0 SYMPOSIUM CONTENT AND STRUCTRE

The symposium included an introductory speech, one keynote, three sessions with eight paper presentations, and a common discussion with SCI-341 and IEEE CogSIMA participants. Just before the final discussion, the Symposium participants had the opportunity to participate in a CogSIMA Keynote.

The introductory speech addressed background aspects, which the Symposium researchers were encouraged to consider during research.

The keynote addressed the following topic: Situation awareness with autonomous systems: challenges and new directions.

The three sessions addressed the following issues:

- Session 1: Situation Awareness and Autonomy — 3 Papers
- Session 2: Human as Systems in the Loop — 2 Papers

- Session 3: Swarm Intelligence and Situation Awareness 3 Papers

The IEEE CogSIMA Keynote addressed the following topic: Human-Machine Teaming: Evolution or Revolution, and the Ethical Dimensions of Cyborgs.

The discussion addressed the following topics: How can the communities of the IEEE CogSIMA and the NATO SCI Symposium work together, and on what topics?

3.0 INTRODUCTORY SPEECH

K. Salm, Permanent Secretary of Ministry of Defence, Estonia

The speaker pointed to the significance of research supporting NATO to defend their partner nations. The following issues were identified as important for the Symposium and the associated research activities:

(1) Autonomous systems gain importance as people become more difficult to recruit. (2) Today's societies are much less tolerant to exposure to threats. (3) Early warning is an important capability. (4) There is a lack of a public market for technical systems supporting public security. Hence, development costs usually do not amortize like for technical systems provided for the public.

4.0 KEYNOTE 1: SITUATION AWARENESS WITH AUTONOMOUS SYSTEMS: CHALLENGES AND NEW DIRECTIONS

Dr. M. Endsley, SA Technologies, United States

Dr. Endsley started with the definition of SA as an ongoing loop: "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" [2]. SA is today relevant in many domains. Considering AS, Dr. Endsley summarized that they require intelligent, robust and reliable technical realizations, which to date and presumably in the near future will be very limited. Admittedly, the recent step from logic for pre-defined situations and classes to learning and adaptation improved the capabilities of AS. However, the ability to predict outcomes today only works for a limited set of programmed or learned situations as set of rules, cases or training data are limited. Moreover, in a noisy world, machine vision/perception is easy to trick. Without a model of reality, AI/deep learning lacks flexibility, adaptability and transparency [3]. Hence, the question is, How can we interact effectively with such systems despite their limitations?

In this context, synergistic human-autonomy teaming is critical to success. Humans provide robust decision making for unexpected events and situations, hence, they are needed alongside with the AS. The human must oversee what the system is doing, intervene when needed, and coordinate and collaborate on functions. SA requires good understanding about the system. If the human is out-of-the-loop, SA is low on how the automation is performing; hence, problems with the system or the automation are slowly detected. Furthermore, to regain understanding of what the system is doing and taking over manually works slowly, too. Loss of SA affects vigilance, monitoring (as monitoring is boring) and trust. There occur changes in information feedback: With automation, things get lost and have to be added again. In addition, the level of engagement affects SA, if the human is mainly passively processing (like a "passenger") because automation is available.

The effect of automation to human performance varies based on what aspect of the task is being automated. In the normal DSA-Decision-Action Loop, SA influences the Decision, which in turn influences Control Execution. Now, if Task Execution is automated, SA will get lower, and cognitive workload increases if intervention is needed; re-engagement-cost is high. If Decision Making is automated, option generation/selection works either as “Approval to act” or “Act unless Veto”. Again, human re-engagement costs are high. If the system decision is correct, automation is beneficial; if the system decision was incorrect, the human might make more mistakes than without automation.

If automation is used to support SA, no human disengagement and no re-engagement costs occur. Benefits for levels 2 and 3 SA are, e.g., providing support for monitoring, information gathering and transformation, reduction of unnecessary searching, sorting, transformations, reducing working memory demands and Direct attention. Information cueing benefits when system is correct, but it is biasing if the system was incorrect.

Dr. Endsley then pointed to the Automation Conundrum [4], in short expression: The more autonomy, the worse the SA. The solution is either a completely robust system, or the support of attention allocation and engagement. The objective is to provide informed trust (How much confidence do I have in the system?). The proposed solution is to provide Shared SA. As the SA of two different persons can be different due to different mental models, the quality of the GUI matters. In order for the human to understand and to project, automation transparency is required. The human must know (1) What does the automat know about the situation? (2) What is it currently doing? Here, real-time requirements are necessary. (3) Why does it do what it does? (4) What will it do in the near future? (5) What are its performance limits? Is intervention necessary? The problem is that the automat is not aware of its limitations. A means to support shared SA is transparency. Proposed goals for Transparent AI & AS Interfaces are understandability, predictability (near future to intervene?), system reliability, system robustness (ability to handle current and upcoming situations), and display persistence (real-time, ongoing reinforcement and presentation of information).

Current UAV operations mostly involve remote piloting or control. Accidents and mishaps occur because of human factors shortcomings in GUI design. Challenges for SA with UAVs are on Level 1 SA poor data (e.g., time lags, noisy data), causing problems with localization and orientation, and limited ability to get needed information. Challenges on Level 2 and 3 SA are poor GUIs, little support for team tasks, and automation (out-of-the-loop problems, understandability of actions/intentions), causing overload and poor understanding and projection of actions.

Based on the knowledge about automation and UAVs, future operations with swarms require the human operator in the role of a conductor (today individual control of each UAV, or supervisory control with one operator controlling several semi-automated UAVs). With a conductor, the UAVs exhibit fully automated team behaviors including collision avoidance, coordinated movement, distributed tasking. The conductor handling group control is responsible for high level planning & strategic oversight (e.g., targeting, course of action, density, speed, and recall). For this, the conductor must understand the behavior of the UAV swarm as a whole. Challenges on Level 1 SA include overload, delayed communications/bandwidth, and time lags. On Level 2 SA, the issue is feedback, on Level 3 SA, unexpected emergent behavior. In order to understand swarms, we may need swarms dedicated to supporting the SA of swarms: a high-level swarm, which supervises all swarms, which are operating each on a specific location. This requires, e.g., mission planning, prediction of actions/paths/timing, and simulated effects of possible changes.

To conclude, the Keynote emphasized that there is a need to develop robust, reliable and transparent autonomy. To maintain SA and manageable workload requires careful design of system interface and automation paradigms. Shared SA is necessary to provide effective human-autonomy teaming. Overall, the keynote provided a framework indicating where the difficulties and the research topic lie.

5.0 SESSION 1 - SITUATION AWARENESS AND AUTONOMY

The first session, Situation Awareness and Autonomy, included three paper presentations.

5.1 Paper #1: A Comparison of Distributed and Centralized Control for Bearing Only Emitter Localization with Sensor Swarms

H. Schily, F. Hoffmann, A. Charlish, Fraunhofer FKIE ,Wachtberg, Germany

Sensor swarms have the potential to enhance situation awareness. If multiple assets in sensor swarms cooperate, there are two challenges: optimizing sensor deployment and minimizing operator workload at the same time. If managing the sensing tasks of individual assets overloads the operator, sensors need to adapt their behavior automatically. There are several possibilities how to implement the control structure.

The contribution provides an investigation on path planning. The task to accomplish is localizing multiple targets with two sensor platforms carrying bearing only sensors. The authors argue that, "Solving the path planning problem through target assignment algorithms is especially interesting since there exist approaches on solving linear assignment problems on distributed systems, only connected through a dynamic communication graph" [5, 6]. The authors compared six different control strategies: Distributed Tree Search (DTS), Distributed Optimizer (DO), Distributed Iterative Exchange of Plans (DIEP), Central Tree Search (CTS), Central Optimizer (CO) and Central Assignment (CA). The comparison considered two aspects: the time until all targets in a scenario are localized, and the necessary computation time.

Central control means to evaluate the joint action space of all sensors/platforms carrying sensors and to assign the best actions to each individual sensor carrier. This approach requires strong computational power as a high dimensional problem must be solved. The authors propose planning the action for each platform locally. With this decentralized approach, coordinated behavior on a joint task for multiple sensors is achieved where each platform computes its own control vector and sends to the others. This procedure is repeated until the solutions converge. Decentralized approach usually not provide an optimal joint solution.

In the evaluation, the targets were considered threats; hence, the platforms were required to stay a threat distance away from the current target estimates. Moreover, the planning horizon h/I (*h* total number of actions, *I* number of times steps with constant control input) of the different algorithms is varied (noted by a number as suffix to the acronym, e.g. DTS3). Figure 1 shows the three evaluation scenarios: *Angle* and *Horizontal* / *Vertical*, *Circle 4* and *Circle 8*. Two distinct starting configurations (*Same* and *Opposite*) were used. All simulations used 100 Monte Carlo runs. Chapter 2 of the paper [5] provides the detailed evaluation design.

The results were as follows. Overall, the CA3 shows promising results: It performed best for the *Angle*, the *Horizontal*/*Vertical*, the *Circle-4,* and the *Circle-8-Same* scenarios. For *Circle-8-Opposite*, "the CA algorithm struggles to find the optimal assignment (…). This is, because the platforms are not next to each other when deciding, if they visit the targets clock or anti clockwise." For this scenario, DIEP and CP3 performed best. The DIEP performed similar to the central planners with the same time horizon. Since it required lower computational costs, it is considered an interesting alternative to the central planning of paths. For each method, a longer planning horizon was beneficial for the outcome.

The authors argue that the CA algorithm "appears to implement a good compromise between centralized and distributed planning methods. Its only weakness, in the experiments conducted, is the simultaneous localization of many targets that are distributed uniformly in all directions with respect to the starting point of the sensor platforms (*Circle* 8)."

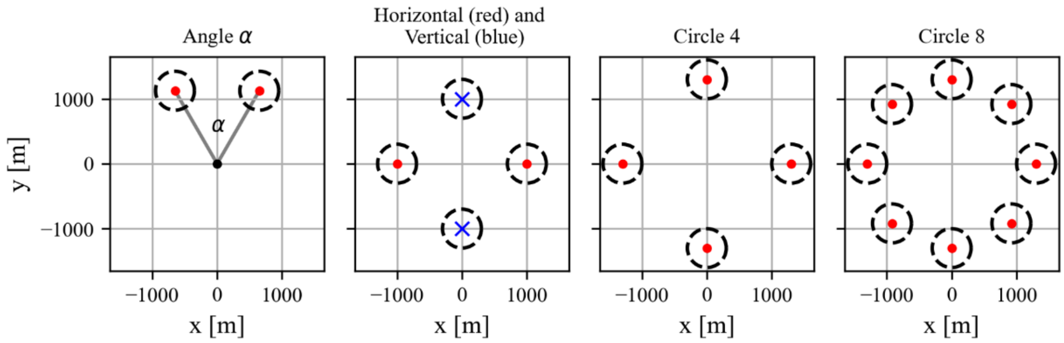

Figure 1: Evaluation Scenarios [6].

5.2 Paper # 2: AI-Powered High Resolution Weather Intelligence Platform

R. Goffer, R. Sahaf, Tomorrow.io, Boston, USA

Environmental SA includes weather information of all kinds, for example, wind, precipitation, temperatures or clouds. They dictate the capabilities of a UxV in a given area. Hence, they are critical in real-time as well as forecast. Anticipation of and adaption of weather situations is even more beneficial for "(…) swarms of UxVs, where each vehicle's situational awareness (SA) is heavily dependent on another's" [7].

For high quality weather forecast, observations (ground, air, satellite), models (global, continental) and high-performance (numerical weather prediction, massive parallel computing) computing are necessary. In areas where swarms of UxVs operate, weather or radar stations might not be available or might sample above the relevant airspace. Moreover, weather models of those areas might not be available, too. The contribution addresses this problem by proposing a high-resolution weather intelligence platform; Figure 2 shows the user interface. The data come from a variety of "traditional and non-traditional sensing technologies". The models are able to ingest different data sources, including the UxVs sensors. In doing so, "(…) a complete picture of real-time flying conditions at sub-kilometer spatial resolution (…)" [7] with high-frequency temporal updates can be provided. In data-sparse regions, the UxVs "(…) could create a stand-alone "network" of weather observations" [7]. Using the Comprehensive Bespoke Atmospheric Model (CBAM), forecasts up to 14 day are possible. The proposed system provides several benefits for UxVs operations, including rapid-update, Multi-Sensor UxVs Weather Analysis and High-Resolution Historical Baseline Analyses and Forecasts. UxVs Tracking and Ingestion of In-Situ Data support the human operators in real-time decision-making. Moreover, insights and alerts derived from the high-resolution data could support the human operators in situations where decisions have to be made quickly. The development and launch timeline is planned to run from the year 2019 to 2025.

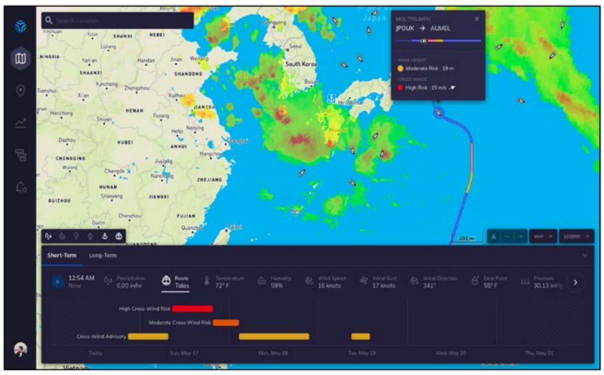

Figure 2: Tomorrow.io Weather Intelligence PlatformTM [7].

5.3 Paper #3: Synthetic Environment for Robotics and Autonomous Systems

M. Biagini, Cap. S. De Mattia, M. Pizzi, Col. M. Turi, LTC B. Koerner, M. Picollo

The authors present a prototypical architecture of Modelling and Simulation tools enabling experimentation on Robotic Autonomous Systems (RAS) and Robotic Swarms. The architecture is open, scalable, modular and standard-based. The objective is to enable testing of "simulated robotic platforms in military operational environments with related countermeasures" [8]. It is developed within the frame of the Research on Robotics for Concepts and Capability Development (R2CD2) project and extends the "C2SIM standard to Unmanned Autonomous Systems (UAxS) for the exchange of orders and reports between Command & Control (C2) and simulation systems" [8].

The R2CD2 2nd generation realized a tactical network and cyber effects capabilities. The latest generation R2CD2 EVO (Figure 3) includes "virtual simulation, a real Ground Control Station (GCS) for real and simulated Unmanned Aerial Systems (UAS) and a C2 system to provide a RAS/Swarm COP that includes the cyber layer" [8]. It allows analyses and counter-measure to RAS systems and swarms.

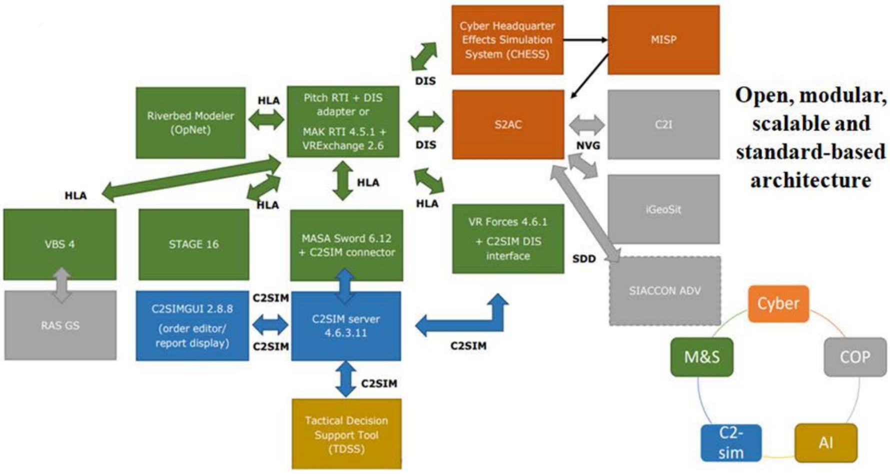

Figure 3: Complete architecture of the R2CD2-EVO project [8].

An implemented scenario in urban environment (future mega-city model - WISDOM) includes war-gaming concepts to RAS and is useful for training of RAS personnel. The system supports "Concept Development Experimentation, Training and Exercise activities on multi-domain UAxS both for NATO and nations" [8].

The realization of a Robotics and Autonomous Synthetic Environment (RAS-SE) strives to provide a homogeneous environment including M&S tools and expert systems. Interconnected, they "(…) provide a Virtual Constructive simulation capability adding to the architecture expert tools (AI driven application like TDSS – Tactical Decision Support System) and C2 Systems" [8]. The RAS-SE can be utilized "(…) to verify, validate, and test the use of RAS in military operations of different types" [8], both technological ones and doctrinal ones, and besides taking into account human-machine interaction.

RAS-SE architecture is based on the R2CD2 EVO architecture and extends the simulation capabilities by integrating the following simulators: VT MAK/VR Forces, Presagis/STAGE, Bohemia Interactive Simulations /VBS4, and C2SIM client-server communication for emulating communication with a SISO-compliant protocol. Interoperability between the simulators works using the HLA (High Level Architecture – IEEE 1516) and Distributed Interactive Simulation (DIS) protocols.

The RAS-SE is extended with a cyber recognized picture informative layer (MSaaS architecture). It enhances robotic SA as it considers "(…) the impact in multi-domain operations and the needs for a comprehensive Common Operational Picture at tactical and operational levels" [8]. This way, the RAS-SE becomes a real synthetic environment where a cloud-based infrastructure makes applications and services available 24/7. Moreover, the cyber effects services architecture allows proof of concepts from effect of the cyber electromagnetic domain (CEMA) (e.g., to protect friendly robots, to attack hostile unmanned robots). Track of the simulated robots on the battlefield and their cyber status information layer can be visualized on C2 systems and COP viewers.

Furthermore, the RAS-SE project implementation integrated the constructive simulator MASA SWORD in order to demonstrate its capability in support of Computer Assisted War-games (CAW). The built-in analysis features were tested in order to assess their usefulness for "(…) future deployment of autonomous robotic platforms in operational environments operating with military land units in combat, combat support and combat service support activities" [8] with a time horizon to the year 2035 and beyond. RAS-CAW "(…) could be carried out with different teams operating with different simulators (human in the loop), or by taking advantage of using a platform (i.e., constructive simulator) where it is possible to plan the operation by teams and then to execute the CAW" [8].

Moreover, the RAS-SE could be used to develop concepts and behavior models, which are ported to real RAS platforms. The authors provide a list of useful steps. Integrating the real world to the simulated world is essential for RAS systems, which must be able to operate reliably in diversified operating contexts. Thereby, the modelling of the sensors is fundamental as they effect the changes of an autonomous platform from in behavioral state into another. In chapter 5 of the paper, the authors provide one diagram showing how the RAS capability development process could work; a second diagram shows the interrelated cyclic simulated real-world process. The RAS-SE architecture design is still under development. A first prototype is available and supposed to be used with CAW activities in support of the Italian Army RAS CD&E campaign.

6.0 SESSION 2: HUMANS AS SYSTEMS IN THE LOOP

The second session, Humans as Systems in the Loop, included two paper presentations.

6.1 Paper #4: Swarm View: Situation Awareness of Swarms in Battle Management Systems

L.-F. Bluhm, C. Lassen, L. Keiser, J. Hasbach, Fraunhofer FKIE, Wachtberg, Germany

The authors address the issue of ergonomic display of human-swarm interaction, focussing on swarms in battle management systems. With increasing size of UAV swarms (e.g., up to several thousands of Tactical UAS [9]), the situation picture may quickly become complex and cluttered. Hence, there is a need for solutions that are still able to provide SA for the owner of the swarm avoiding information overload.

First, the contribution provides the results from a literature survey. On the one hand, the authors extracted the challenges that might arise when a single human operator has to monitor a large swarm: complex operational picture, high dynamics, information overload, and increasing demand on the user. On the other hand, they provide existing guidelines for ergonomic display design. Based on that, the authors designed four different application-oriented prototype layouts, optimized for mouse, keyboard and touch input:

- Leader-based representation: Swarm divided into teams; visualization of the leader robot of a team.
- Swarm-based representation (**Figure 4**): Entire swarm as one unit; visualization of the entire swarm, single robots detachable.

- Area-based representation: Visualization of areas, POIs etc.; interaction with environment.
- Zoom-based representation: Visualization depending on zoom level; user decides information level.

All layouts comprise six main components, which are adapted to the respective layout. The Map (1), based on Google Maps (2021) is the basis and located in the display center. It provides functions like zoom, a mini-map, Blue and Red Forces with additional information, unknown objects, and an option for areas and points of interest (POI). The Territory Management (2) allows the user to create, e.g., areas of operation (AO) or POIs. The Task Management (3) contains a timeline with all scheduled, current and completed tasks and allows planning new tasks for the swarm or parts of it. The Status information + Livestream (4) show the status of the swarm or UAV. The display size of the livestream (from a selected UAV or area) is variably adjustable. The Red Force information (5) displays unknown and known objects in a separate list (in addition to the map display). An assistance system prioritizes incoming objects supporting the user's decision-making. The Dialog (6) displays incoming alerts, warnings and messages.

The four layouts will soon be evaluated with focus groups from the German Army Reconnaissance Force. Based on the feedback from specific military roles and hierarchy levels, the layouts will be iteratively adapted. Further developments/experiments will determine SA, user experience and intuitiveness (laboratory and field tests) and derive recommendations for cross-design and swarm interaction user interfaces.

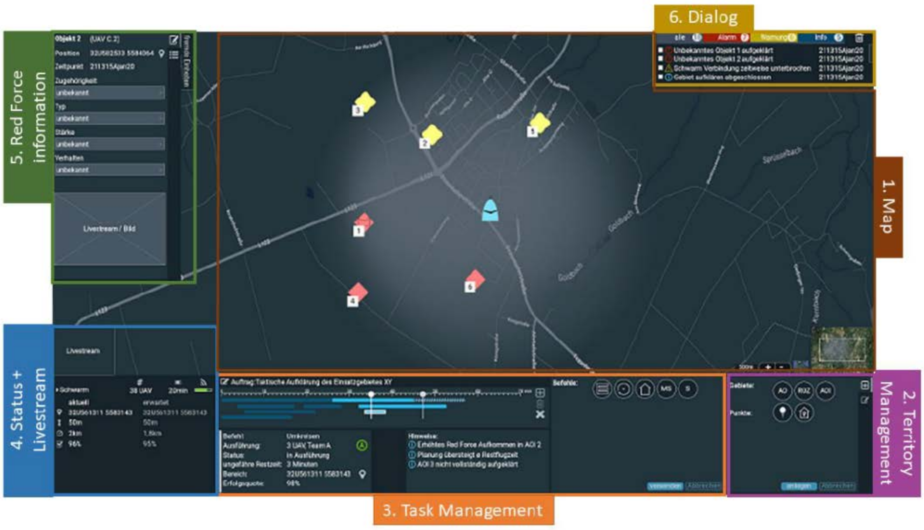

Figure 4: Visualization Components [10].

6.2 Paper #5: Anomaly detection and XAI concepts in swarm intelligence

M. Anneken, M. Veerappa, N. Burkart, Fraunhofer IOSB, Karlsruhe, Germany

The authors address the issue of information overload occurring due to the large amount of data shared by autonomous systems. In order to mitigate this problem, they propose to assist the human operator with two ways of intelligent data analysis. The first approach is automated anomaly detection, which might strengthen SA of the human operator and decrease their workload. The second approach is eXplainable Artificial Intelligence (XAI) concepts; they have the potential to make swarm behavior as well as the anomaly detection results more understandable.

The authors argue that controlling a swarm of drones is still challenging. On the one hand, the (semi-automated) swarm agents "have to decide on a course of action" [11]; on the other hand, the human operator has to decide on their actions, e.g., to interact with the swarm. The suggestions of the contribution strive to improve the human-in-the-loop. Considering the application of maritime surveillance, a dynamic approach with non-stationary agents has several advantages. First, some scenarios are only manageable using a dynamic approach; second, agents are less expensive compared to stationary surveillance sensors; third, using the agents flexibly at multiple locations could decrease the amount of personnel required for operating the swarm. However, situation assessment still will require informed human operators.

The authors argue that anomaly detection algorithms used in the maritime domain for vessel analysis might be applicable to swarms introducing the following scenario. “Let’s say, we have a swarm in support of maritime vessels, these vessels will collect not only the data available by their own sensor systems, but by all assets. The information gathered by all sources needs to be fused into one coherent picture. This should not be limited to the first level of JDL data fusion, but should include higher level data fusion processes in order to elicit the available information about all objects in the vicinity.” [11] Data-driven and signature-based approaches are able to cope with such situations. The literature provides three approaches for detecting positional and kinematic anomalies: Statistical interpretation as an outlier compared to normal behavior; cluster analysis clustering similar trajectories and exact routes; deep learning approaches for modelling normal moving patterns. To cope with more complex scenarios, algorithms including the context around the vessel (infrastructure, geography, weather etc.) are necessary. In the case of certain complex anomalies, distinguishing between normal and abnormal behavior requires rule-based, fuzzy-based, multi-agent or algorithms based on probabilistic graphical models. For all mentioned algorithm categories, the authors point to a great number of example algorithms.

Some of the algorithms are black-box models and, hence, their interpretation is complicated for a human operator. XAI concepts can help mitigate this issue. XAI concepts intend “to provide ethics, privacy, confidence, trust, and security” [11], and strive to clarify the decision-making in “what it has done, what it is doing now, and what will happen next” [11], thus improving the SA of the human operator. Considering XAI models, model-specific methods (limited to certain mathematical models) can be distinguished from model-agnostic (applicable to any type of model) methods.

In the present contribution, the focus is on model-agnostic methods. Considering those, local explanation methods (explaining a single prediction result over the entire model) can be distinguished from global explanation methods (explaining the behaviour of the entire model, e.g. in the form of rule lists). Moreover, the authors distinguish methods using Feature attributions, Path attributions, and Association Rule Mining. With feature attributions, “users will be able to understand which features their network relies on” [11]; method examples are the Shapley Additive Explanations (SHAP) providing global as well as local interpretability and the Local Interpretable Model-agnostic Explanations (LIME) indicating “the input features the model considers when making a prediction” [11]. Path attributions like the Path Integrated Gradients (PIG, using local explanation) provide the features, which contribute most toward model prediction, thus giving insight into the reasoning that led to the decision. Association Rule Mining (ARM) is another method using global explanation. It “(…) finds correlations and co-occurrences between features in a large dataset” [11]. ARM methods use simple if-then rules and therefore are considered as most interpretable prediction models. The techniques Scalable Bayesian Rule Lists (SBRL), Gini Regularization (GiniReg) and Rule Regularization (RuleReg) are considered suitable application in surveillance tasks [12].

The authors argue that using such XAI concepts, human operators (decision-makers) could get better understanding, better control, and better communication with swarms of autonomous agents, particularly in challenging environments. Altogether, applying the two methods of anomaly detection and XAI concepts for the human-in-the-loop, user understanding and trust towards swarm intelligence might improve.

7.0 SESSION 3: SWARM INTELLIGENCE AND SITUATION AWARENESS

The third session, Swarm Intelligence and Situation Awareness, included three paper presentations.

7.1 Paper #6: A New Swarm Collection Tasking Approach for Persistent Situational Awareness

J. Berger, N. Lo, A.-C. Boury-Brisset, Defence Research Development Canada, Quebec, QC, Canada

The authors introduce an approach for swarm collection tasking for mobile ad hoc agents in ISTAR (intelligence, surveillance, target acquisition, and reconnaissance). The objective is to utilize the agents in order to enhance persistent situational awareness, with the agents bridging the gap between information need and information gathering. For this, it is necessary that the semi-autonomous agents cooperatively achieve collection tasking and execution. The challenge is to achieve this despite the on-board limited processing power and energy budget. Figure 5 (left) shows a typical collection tasking context: “It defines a grid cognitive map representation reflecting situational awareness over a specific region of interest, capturing prior knowledge, belief and/or known probability distribution on cell occupancy and target behavior” [13].

The presented swarm collection tasking approach proposes centralized collection planning, episodically mediated by a swarm leader; plan execution, however, is done decentralized. In a nutshell, “The approach combines a new compact graph representation and a sound approximate decision model to perform sensor agent path planning optimization, subject to periodic connectivity in order to achieve information-sharing, fusion, situational awareness and dynamic retasking/planning” [13].

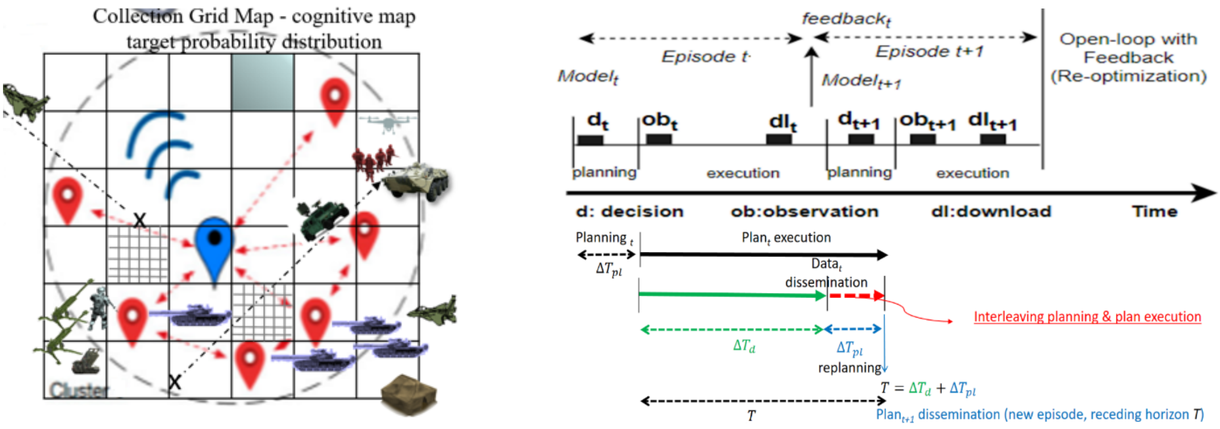

Figure 5: Left: Swarm Collection Tasking Context. Right: Open-loop with feedback collection tasking optimization over receding time horizon T [13].

The new open-loop with feedback decision model (Figure 5, right) for collection planning maximizes the collection value over a receding time horizon. Periodic swarm connectivity supports observation dissemination, data/information fusion, situation assessment and replanning at the sink node. Periodical maximum collection dissemination to a sink node regards the energy constraints. The communication planning/routing scheme, which disseminates the collection, utilizes a minimum spanning tree to minimize energy consumption. For details including related figures, please see the extensive paper sections in chapter 3 of the paper.

Due to the authors, the proposed approach extends a swarm’s ability to better meet task demand and allows significant expansion of the observed areas. “The new problem formulation also paves the way toward a computable upper bound on solution optimality, if exact problem-solving methods are used” [13].

7.2 Paper #7: A Framework Based On Deep Learning Techniques For Multi-Drone ISR Missions Performance Evaluation In Different Synthetic Environments

A. Antenucci, L. Messina, A. Palumbo, S. Mazzaro, W. Matta

The authors investigate the application of Deep Neural Nets to simulator engines. They use an experimental approach in order to find out (1) "(…) how neural networks trained on real datasets, on-board of one or more drones, behave in different synthetic environments" [14]. They created an operational interface, which is able to acquire live video streams from drones. They consider the environments VRForces, ROS Gazebo, and VBS4 to find out how the amount of graphical detail will affect accuracy and precision-recall curves. The objective is the detection of certain object classes (e.g., people, vehicles). As a testbed, the AI-Enabled Command and Control (C&C) system "SWARM" is used.

Using synthetic environments has several advantages. Real datasets often comprise low variability and may lack precise annotations. In contrast, simulation allows the definition of infinite scenarios and accurate 3D and 2D annotations, and has advantages for model evaluation and alleviation of bias. Moreover, simulation can help overcome obstacles related to privacy issues.

Figure 6, left, shows the Simulation System Architecture. The experimentation framework contains three synthetic environments. For VBS4, a plug-in generating a synthetic scenario with one or more drones was realized. Each drone is equipped with a virtual camera capable of generating a video stream. For ROS Gazebo, the "(…) images were acquired using an Iris drone (…) equipped with IMU and a camera configurable via file and implemented as a C ++ plugin". A similar plug-in was realized for the VR-Forces environment. The scenario views of the three environments were standardized using the Pinhole model to achieve the same viewing characteristics.

Figure 6: Left: Simulation System Architecture. Right: Example of annotations in visdrone dataset in a Multi-drone ISR Mission [14].

Utilizing synthetic images alone might introduce new biases. Hence, the authors applied classical computer vision and image manipulation methods to identify differences between the objects detected in the images of the VISDRONE dataset (real) and those identified in the three simulators. Contour extraction of people and vehicles as object classes showed a loss of information compared to real data.

The evaluation scenarios used an urban context with people, vehicles, roads, houses, and vegetation. The flight plans comprised low speeds (1-3 m/s), a ground altitude of 5-30 m and stationary weather conditions. The acquisition of the payload video streams used a frame rate of 30 fps. Three versions of TFRecords (standard Tensor Flow data format) were generated (filtering applied to the area of the bounding boxes: non, 100 px, and 200 px). All three test-sets contained 6 object classes (person, car, van, truck, bus, motor).

11 DNN models were considered, using Tensorflow as AI framework. The large data-sets COCO, KITTI, and VISDRONE were considered as pretrained datasets. The best results were achieved using the Fastern RCNN Resnet (pretrained on VISDRONE dataset). VBS4, having the best graphics engine of the three simulation environments, is the one that comes closest to reality (Figure 6, right). Overall, the synthetic environment proves to be a good test bed for neural networks trained in the real world (ca. 80% accuracy in the best case).

7.3 Paper #8: Interacting Swarm Sensing and Stabilization

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Recently, swarm theory investigated in biology and physics has been put to robotic platforms including the application of swarms for defense. While related work focusses on single swarm behavior, this contribution extends the investigation to multiple, interacting swarms, and their resulting patterns. The authors provide a theoretical approach investigating the collision of two swarms with non-linear interaction. The objective was to predict under what circumstances the two swarms could combine to form a mill after the collision of two flocks. The background to this question is the need in certain military scenarios to redirect or capture a swarm.

Figure 7, left, shows that the state after collision depends on the collision angle as well as on the coupling strength. **Figure 7**, right, shows an example where two swarms, initially in flocking states, approach a milling state. The reason for this behavior is, that "As the two swarms approach, (…) each agent begins to sense the forces of intra-agent swarmers, causing the two swarms to rotate around each other while maintaining an approximately constant inter-swarm density. Over time the two swarms slowly relax to a well-mixed milling state composed of uniformly distributed agents from both" [15].

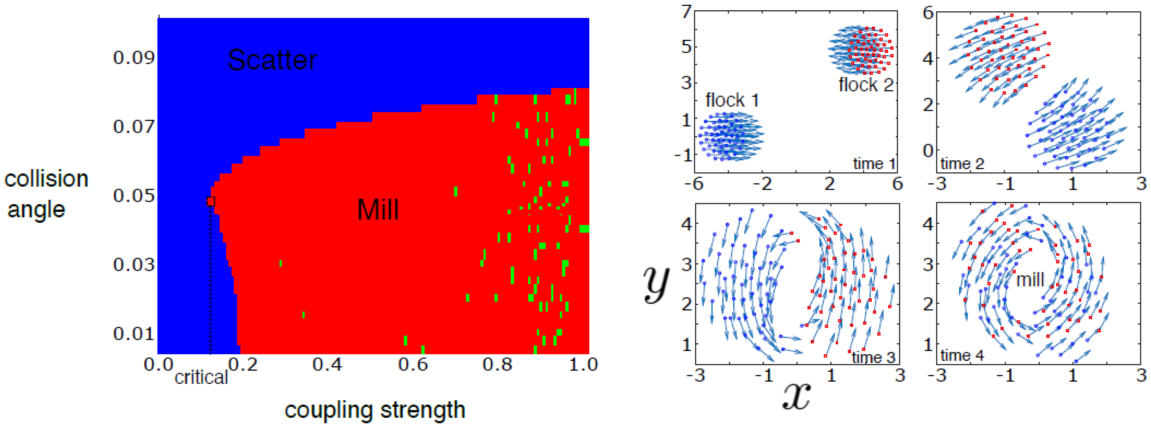

Figure 7: Two Swarms colliding [15].

The applied analytical methods "(…) rely on the assumption that, upon collision, two swarms oscillate near a limit-cycle, where each swarm rotates around the other while maintaining an approximately constant density" [15]. Using a rigid-body approximation determining the stability of limit-circle states, predictions could be made which only depended on physical swarm parameters. This provided "(…) a lower-bound on the critical coupling for small collision angles" [15]. For symmetric flocks (with equal numbers and physical parameters), the transition point from scatter to mill "(…) was similar to an escape-velocity condition in which the critical coupling scaled with the squared-speed of each flock, and inversely with the number of agents in each flock" [15].

The theoretical predictions were confirmed in preliminary colliding swarm experiments using a mixed-reality setup containing 5-8 Crazyflie micro-UAVs. The experiments considered scenarios with 8 real + 8 simulated robots, 5 real + 45 simulated robots, and 50 simulated robots. For all scenarios, a stationary mill was observed. The preliminary results show that “(…) we can have one swarm capture another based on the physical parameters chosen” [15]. Moreover, based on known parameters and swarm sizes, it should also be predictable “(…) when colliding swarms will not form a milling state” [15], i.e., one swarm cannot capture the other. Future work will address how to get into scattering state, or to remain in flocking state, as well as include the effects of communication delays or internal and external noise effects into the theory.

8.0 KEYNOTE COGSIMA: HUMAN-MACHINE TEAMING: EVOLUTION OR REVOLUTION, AND THE ETHICAL DIMENSIONS OF CYBORGS

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Human-machine teams are proposed to be a growing force in military capabilities. The speaker distinguished three waves of human-machine teaming. Wave 1 comprised simple automated/cognitive tools like traffic lights. Wave 2 comprised complex automated/cognitive tools like Ground Collision Avoiding systems. Wave 3 is supposed a human-machine symbiosis; in this context, it is noticeable that robots can share their memories/mental states in real-time and communicate without speaking. The speaker expects wave 3 to happen as an evolution, not a revolution. Besides the technical issues, there is “a much-needed conversation about the ethical dimensions of the warrior-autonomy teaming enterprise” [16]. Besides, it could be possible that “autonomous agents and the soldiers they serve can not only engage in morally praiseworthy conduct, but also actually improve decision quality from the prudential and moral perspectives both”[16]. For human-machine teams making the best joint decisions, the key concept of an "artificial conscience" is proposed. The speaker provided “what an artificial conscience would look like, and how we could develop one” [16].

Key aspects were the following. An artificial conscience should work as a critical faculty in decision making for autonomous systems. It could include aspects like moral sensitivity, judgment, motivation, and skill as well as principles of reason from traditional moral theory (character, consent, and consequence) as well as universal frameworks. The speaker referred to various philosophers and their concepts: character (concerned with skills one needs to flourish as a person): Platon, Sokrates, Konfuzius; consent: Kant; consequence: John Stuart Mill/Consequentialism. Reasons for building an artificial conscience are, e.g., that autonomy is inevitable, or allied military doctrine (e.g., humans have always to be in the loop) and morality demand it. In this context, the speaker referred to a book on national security law dimensions of AI-infused systems [16]. A helpful means when building an artificial conscience could be the cognitive bias codex [17]. Among the concerns and rejoinders were (1) What values should be included? (2) It is not possible to build an Artificial Conscience (3) Trust and Transparency may lack, hence, AC would be rejected.

9.0 COMMON DISCUSSION WITH SCI-341 AND IEEE COGSIMA

The discussion started with the statement that the two events – IEEE COGSIMA and the SCI-341 Symposium – were planned to cover similar dates in order to make it possible that both communities interact. Then, a representative of the COGSIMA gave a short overview on the COGSIMA community and history, as well as about this year’s topics [18]. After that, the representative of the SCI-341 Symposium gave an overview on this year’s SCI-341 Symposium and the addressed topics.

As possible further interactions were proposed (1) the SCI community engaging in CogSIMA workshops, e.g., on interoperability; (2) a joint session next year (Salerno/ITA); (3) a joint research group, e.g. on collective intelligence or autonomic systems collaboration; (4) Linking the Human Factors Panel with the SA Panel; (5) Implementing an Exploratory Team (and to write a TAP).

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