Multi-Partner Project: Safe, Secure and Dependable Multi-UAV Systems for Search and Rescue Operations

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Abstract*—Unmanned Aerial Vehicles (UAVs) have become essential in search and rescue operations, especially in disaster management scenarios. Their effective navigation and the integration of a plethora of sensors assist in efficient person detection, making them an essential technological tool to first responders. Multi-UAV systems extend these benefits by using coordinated strategies to cover large areas efficiently, reducing overall mission response time and enhancing its success. Despite these advantages, challenges remain in ensuring the safety, security, and dependability of (mutli-)UAV missions. Issues such as navigation risks, potential cyber threats, and hardware-/software-related reliability issues can impact the mission results. Additionally, UAVs are highly constrained devices with limited battery capacity, requiring the use of lightweight technologies. In this paper, we present part of the results of the SESAME project, an EU multi-partner project that aims to develop safe and secure multi-robot Systems. In particular, we present some of the developed SESAME Executable Digital Dependability Identities (EDDI) technologies based on Markov models, statistical distance measures, and other advanced approaches for enhancing safety, security and dependability of the UAV platform and underlying models. These EDDI technologies are seamlessly integrated using the ConSerts framework in a multi-UAV platform and tested using search and rescue scenarios. The results demonstrate significant improvements in multi-UAV safety, with an availability rate of 91% and a search and rescue algorithmic accuracy of 99.8%. Additionally, the system achieves precise detection of spoofing attacks, using collaborative localization as a mitigation technique to guide the UAV to a safe landing, even in the absence of GPS signals.

***Index Terms*—multi-UAV, safety, security, dependability, collaborative localization, search and rescue algorithms**

I. Introduction

Unmanned Aerial Vehicles (UAVs) have emerged as valuable tools in search and rescue (SAR) operations, especially in the aftermath of natural disasters, where speed and adaptability are crucial [1]. With high-resolution cameras, thermal imaging, and other advanced sensor technology, UAVs can access challenging terrains and locate people even in conditions with low visibility or limited accessibility, making them ideal for SAR purposes [2], [3].

Building on these capabilities, multi-UAV systems further enhance SAR efforts by leveraging a coordinated approach [4]. Unlike single-UAV deployments, multi-UAV systems can cover larger areas simultaneously, providing faster, more efficient search capabilities through task-sharing and redundancy [5]. By distributing tasks across multiple agents, these systems reduce response times and increase the likelihood of success in time-sensitive missions [6], [7]. In disaster settings, a fleet of UAVs can locate and monitor people, assess damage, and identify hazards, ensuring that ground teams are informed with real-time data as they prepare for evacuation efforts [8].

However, despite the advantages of multi-UAV systems, several challenges remain, particularly in ensuring the safety, security, and dependability of these systems [9]. Safety concerns risks related to UAV navigation in complex or unpredictable environments, where collisions and technical failures could compromise mission success and endanger personnel or civilians nearby [10], [11]. Security issues are also significant, as attacks on communication channels or data feeds could lead to compromised operations or misinformation, potentially endangering lives [12], [13]. Moreover, ensuring the dependability of UAV systems is essential, given the high-stakes nature of SAR operations [14]; any interruptions or malfunctions in UAV performance could delay rescue efforts and hinder coordination, impacting mission outcomes.

Previous studies have explored various aspects of UAV deployment for SAR and the technical requirements needed to ensure safe and dependable operation [15]. Several works in the field have examined autonomous control systems to enable UAVs to navigate challenging terrains without human intervention [16], [17], while others have focused on the development of secure communication frameworks that protect against potential cyber threats [18], [19]. In multi-UAV systems, the Robot Operating System (ROS) is widely employed for command and control functions. The publish/subscribe architecture of ROS enables close integration and reliable communication between multiple agents; however, it also brings certain security vulnerabilities, such as the risk of eavesdropping, man-in-the-middle attacks, and data injection in cyber attack scenarios [20]–[22]. In this context, this paper aims to develop safe, secure and dependable technologies for multi-UAV systems, assessing their potential to improve SAR operations. The main contributions of this paper are the following:

- We present ConSerts, a key integrating technology, alongside other SESAME technologies related to reliability and safety (SafeDrones), SAR accuracy (SafeML, DeepKnowledge, and SINADRA), security (Security EDDI), and dependability (Collaborative Localization) used in this paper.
- We present both in-field and simulation-based results for a use case involving multi-UAVs in SAR missions, evaluating the aforementioned technologies through our developed multi-UAV platform, which integrates the relevant SESAME technologies.
- We illustrate the enhancement of SESAME technologies by presenting various use cases that demonstrate how SESAME technologies can improve multi-UAV availability and SAR accuracy.

II. The SESAME approach

A. Overview

The SESAME project, an EU Horizon 2020 multi-partner project[1], has developed an open, modular, configurable, model-based approach for the systematic engineering of dependable multi-robot systems. The innovative SESAME technologies enable the development of multi-robot systems capable of dependable execution of tasks and missions in open configurations, and in operational conditions of uncertainty that include the potential of cyber-attacks.

At the heart of the SESAME project innovations is a model-based approach where models are automatically composable and also algorithmically analysable at both design time and runtime. SESAME further advances multi-robot systems engineering by providing: (i) Domain-specific languages that hide the complexity and intricacies of robotic simulators and platforms; (ii) Machine Learning based libraries of well-designed scenarios that are adaptable and reusable across applications; (iii) Design-time analysis of safety and security via composition, reuse and automated analysis; (iv) Novel safety and security assurance achieved by shifting part of the assurance to runtime; and (v) Seamless (re)configuration at design and at runtime to easily adapt to changing needs and operating environment.

SESAME builds on a novel and advanced synthesis of the state-of-the-art in model-based development, nature-inspired technologies, and AI data-driven techniques. Model-based techniques are used to capture pertinent engineering knowledge and assumptions about Multi Robotic System (MRS) operation, failures and their effects, in verifiable and executable at runtime models that can be used to assess, verify and ensure security and safety.

[1]https://www.sesameproject.org

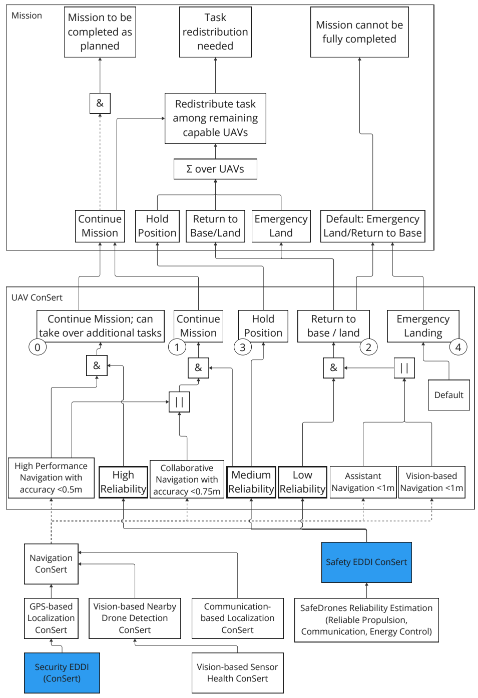

Fig. 1. Overview of hierarchical ConSert UAV network for SAR mission

A key technology that has been developed in SESAME are the Executable Digital Dependability Identities (EDDIs) which constitute model-based artefacts spanning the multi-robot system lifecycle that carry verifiable dependability models of their reference robotic systems produced at design-time, capturing safety and security hazards, their causes, effects and possible corrective actions. SESAME's technologies are versatile and can be applied to many multi-robot use cases, as demonstrated throughout the project. However, in this paper, we focus specifically on one use case: the application of SESAME technologies in multi-UAV systems, showcasing their impact on enhancing reliability, safety, and security in SAR missions.

B. Conditional Safety Certificates (ConSerts) Approach

In the presented UAV use case, we use the Conditional Safety Certificates (ConSerts) approach [23] to evaluate dependable UAV behaviour during operation. ConSerts enables safety, security and, more generally, dependability by incorporating other SESAME technologies and combining their results to assure dependable operation up to the SAR mission level. As Figure 1 shows, ConSerts triggers a number of SESAME technologies (safety and security-specific ConSerts are highlighted in blue color) according to the operating conditions. Only the mission-level and top-level UAV ConSert (per UAV) are detailed, with the rest being encapsulated into single rectangles. At the mission level, a decider is used to propose the outputs of all UAVs and determine whether the mission can be fulfilled or if a fallback like an emergency landing needs to be initiated. For each UAV, a corresponding ConSert model determines whether it can continue operating or if it must abort and return to the base, initiate an emergency landing or hold the position and wait until the critical situation is resolved. This decision depends on the current UAVs' navigation capabilities and the reliability of various internal systems. The reliability of internal systems is determined by the SafeDrones component (Section III-A1), which provides guarantees that represent different levels of reliability for the propulsion, communication and energy control system. Furthermore, the navigation capabilities are assessed based on the accuracy of localization. The precision of the navigation depends on the accuracy provided by different localization components. The GPS localization ConSert relies on GPS-related quality factors and on the security attack detection (Security EDDI-Section III-B). The vision-based localization ConSert relies on the health state of the vision sensor and the SafeML output that determines the reliability of the perception algorithm. The communication localization ConSert monitors the internal signal and connection states to other nearby UAVs.

III. SESAME Technologies

Ensuring the dependability of complex systems, especially those that involve multiple components or are part of integrated networks, presents unique challenges. Although standards and guidelines offer general directions, the specific approach to proving a system's dependability often varies significantly. This variability makes it difficult for certification bodies to evaluate and approve systems effectively, particularly when these systems need to integrate along supply chains or within broader networks [24]. In such cases, ensuring dependability can become costly and time-consuming, with the potential of errors that may undermine crucial system properties.

To address these issues, Digital Dependability Identities (DDIs) were developed as a way to standardize and simplify dependability assessments. A DDI is a structured, modular framework that includes all relevant information about a system's dependability characteristics. The core of a DDI is an assurance case—a clear, organized argument that demonstrates that the system meets dependability requirements. This case links various models and evidence, such as requirements, assumptions, architecture models, dependability analyses, and verification documents, into a cohesive narrative [25].

However, to ensure the dependability of more dynamic, multi-agent systems such as the use case presented here, it is not enough to address dependability solely at design time; when systems can adapt, reconfigure, and behave autonomously, runtime assurance is also required. The Executable DDI (EDDI) is intended to address this problem by extending the DDI concept with runtime components for monitoring, diagnosis, and response. As composable, executable models, they can combine or interact at runtime to adapt and reconfigure themselves, just like the host systems they monitor.

The EDDI collection of models is generated from DDI models during the design phase, activated when the system is first deployed, and maintained throughout the system's entire life cycle. This allows for consistent dependability management as the system evolves. EDDIs are particularly useful for assembling complex systems from multiple parts, whether during the development process or as part of a larger network of systems, enabling smoother and more reliable integration [26]. EDDIs are intended to capture multiple aspects of dependability, including both safety and security.

A. Safety EDDI

Safety elements include causal models such as fault trees and behavioral models like Markov models or Bayesian networks, supporting runtime diagnosis and failure assessment by monitoring symptoms and evaluating evidence. For the UAV fleet and SAR mission, safety aspects are integrated within EDDIs, encompassing hazard analysis and risk assessment. Event monitors detect anomalies that indicate potential failures, which EDDIs interpret to assess impact and propose actions. Distributed across UAVs and the ground control station, EDDIs communicate findings to coordinate actions, such as initiating emergency landings and reallocating tasks. Safety models can be sourced from development tools compatible with the Open Dependability Exchange (ODE) metamodel for seamless export [26]. Safety-related EDDI models [27] are described below:

1) SafeDrones Technology: SafeDrones [28] focuses on enhancing the reliability and safety of UAVs by providing a novel runtime evaluation method. It introduces the concept of complex basic event in Fault Tree Analysis [29]. It has also the capability of considering system's reconfiguration (e.g. reconfiguration in the Propulsion system [30]). This methodology enables UAVs to adapt their missions based on current reliability estimates, thereby improving safety and mission success rates. It serves as a modular runtime safety monitor for UAVs suitable for use in an EDDI. By integrating fault tree analysis (FTA) combined with dynamic Markov-based models (as complex basic events) and real-time monitoring, SafeDrones provide continuous reliability assessments during UAV operations. SafeDrones includes the estimation of the probability of failure, taking into account various components such as the battery, processor [31], and UAV rotors.

2) SafeML Technology: SafeML [32], is an ML-based technology that can be used to detect when the data encountered at runtime is not similar to the data used for training in Machine Learning (ML) models. It does that by evaluating the statistical distance of the (subset of) data distribution. SafeML assesses a sliding window of images captured by UAV cameras against a reference set derived from the model's training images. The greater the dissimilarity between the input and the reference images, the lower the confidence in the ML model's outcome. Varying levels of confidence can then map to specific responses, orchestrated via ConSerts, such as executing a minimal risk maneuver or alerting human operators.

3) DeepKnowledge Technology: Similarly to SafeML, DeepKnowledge [33], is a tool-supported technology that enables systematic testing for computer vision components in autonomous systems. This tool is a whitebox testing technique built on foundational concepts of model generalization [34], and dynamic features evaluation. The key difference is that SafeML evaluates the difference between ML input and training reference data, whereas DeepKnowledge assesses the internal neuron behaviours of the given ML model. The evaluation rigorously examines the model's learning performance, focusing on its ability to capture and generalize complex semantic patterns when data shifts. DeepKnowledge operates in two phases: design and runtime. It assesses model reliability at design time and leverages this at runtime by analyzing image activation traces in the DNN and estimating an uncertainty metric for prediction accuracy. Used for evaluating the robustness of the tiny YOLOv4 model in UAVs for person detection, DeepKnowledge provides a coverage score that captures model behaviour and assess its correctness in dynamic environments.

4) SINADRA Technology: Situation-aware dynamic risk assessment (SINADRA) [35] uses Bayesian networks and enables the system to leverage situation-specific risk factors and causal influences, akin to human decision-making, to dynamically determine risk at runtime. It works with SafeML and/or DeepKnowledge to guide adaptation actions based on current conditions and uncertainties. When person detection uncertainty is high, SINADRA estimates the risk and criticality of missed persons in the SAR algorithm. High criticality prompts immediate re-scanning of an area, whereas low criticality allows UAVs to proceed to the next task. This combination optimizes resource distribution and time efficiency during first-response missions.

B. Security EDDI

The Security EDDI framework is designed to monitor and identify potential cyber-attacks within a target system by leveraging attack trees and real-time alerting. These attack trees, generated during the attack tree creation process, outline all possible attack scenarios based on identified cyber and physical vulnerabilities. Each attack scenario includes high-level information such as ”capecId,” ”title,” ”description,” ”severity,” ”likelihood,” and ”mitigation,” facilitating comprehensive analysis of the target's threat landscape.

Each Security EDDI is implemented as a Python script tailored to a specific attack tree, capable of parsing and recognizing attack patterns to detect an adversary's ultimate goal. Supporting components include an MQTT message protocol broker and an Intrusion Detection System (IDS), which inspects network traffic and publishes alerts upon detecting suspicious activity. These alerts are then published to an MQTT topic, where each Python script listens for relevant alerts. Upon detection, the script's logic navigates the attack tree structure, tracing the attack path from the leaf nodes toward the root. Reaching the root node implies the adversary's end goal is achieved, indicating a critical security event. Though the IDS focuses on cyber threats, the EDDI framework can incorporate additional sensors for physical attack detection, providing a comprehensive, adaptable, and distributed threat-monitoring solution.

To help ensure compatibility and interaction of Safety EDDI and Security EDDIs mentioned above, a runtime Safety-Security Co-Engineering concept has been proposed in [36]. This provides a combined methodology and workflow designed to harmonize the development of the EDDIs and capture system dependability information in a holistic manner.

C. Collaborative Localization

Collaborative Localization (CL) enables multi-UAVs to collaboratively determine and enhance their position and navigation, particularly in scenarios involving GPS signal loss or

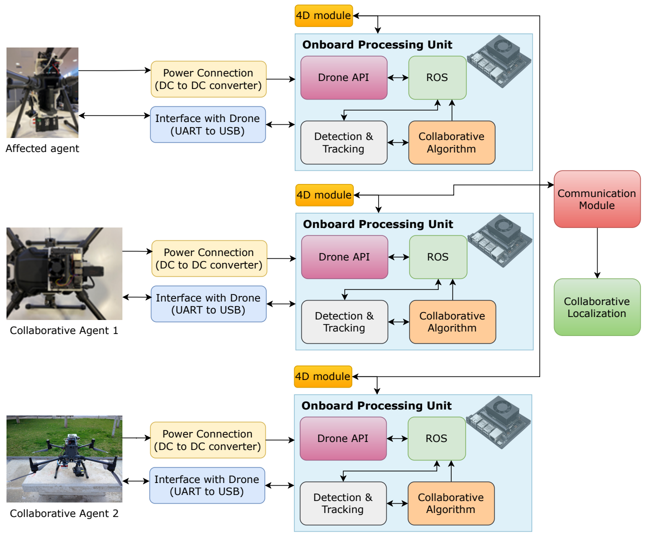

Fig. 2. Hardware and software implementation of Collaborative Localization.

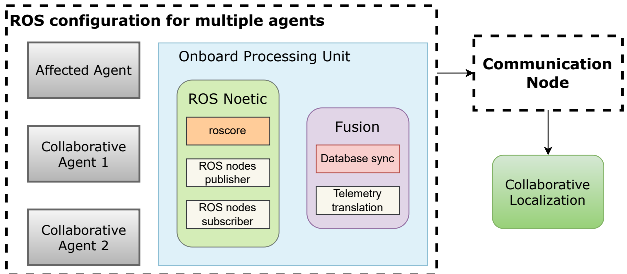

Fig. 3. Real-time UAV detection as a part of the Collaborative Localization tool

sensor inaccuracies due to security attacks [37]. CL allows UAVs to share data for detection, tracking, and positioning, providing alternative navigation for affected UAVs. Nearby UAVs equipped with Jetson onboard devices and RGB cameras detect and calculate distances to affected UAVs in real-time using tinyYOLOv4 and monocular depth estimation [37]. The final position is refined through trigonometric calculations and the Haversine formula [38].

The CL implementation presented in this paper involves a network of three UAVs, as shown in Fig. 2. Each UAV is equipped with an NVIDIA Jetson XAVIER NX for detection, data analysis, and navigation. ROS serves as the middleware to facilitate multi-agent interaction and data analysis, coordinating communication and collaboration among UAVs, as depicted in Fig. 3. This architecture allows the system to effectively process and transmit the position of the affected UAV.

IV. Search and Rescue (SAR) Use Case

UAVs are essential for emergency operations that require high availability, safety, and security, necessitating proper coordination as provided by SESAME project technologies. This use case simulates events to evaluate the Safety and Security EDDIs in a SAR scenario, where person detection algorithms guide operators to rescue individuals at high risk. Evaluations are conducted with and without SESAME technologies for comparison.

A. Multi-UAV Control Platform

The Multi-UAV platform is designed to provide a modular, extendable, scalable, stable and reliable infrastructure to enable

Fig. 4. SESAME multi-UAV platform with the three UAVs operating the SAR algorithm and the integration of SESAME EDDI technologies

end-users to specify functional and non-functional requirements. It is focused on enabling the connection, communication and control of multiple UAVs as well as on hosting multiple algorithms such as UAV routing and computer vision. The system architecture consists of five main layers with different components. Each layer is briefly presented below:

Graphical User Interfaces (GUI) provides user-friendly access to the UAV platform, designed to be lightweight in processing and intuitive. Two GUIs are available: the web GUI for monitoring UAVs via any browser, showing operations, positions, and video feeds; and the control GUI for first responders to command and manage multiple UAVs, offering all the web GUI features plus task assignment capabilities.

UAV Ground Control Stations automates the logging, management, and monitoring of UAV operations to support mission goals such as maximizing area coverage, improving communication, reducing evacuation time, enhancing safety, and minimizing operator workload. These platforms offer features like real-time performance data, flight control, task uploads, parameter settings, and live video monitoring, supporting various UAV types across different platforms.

Database manager provides an API for database access, allowing UAVs and software clients to make asynchronous data requests. It verifies that requests come from within the network to prevent external access. For instance, UAVs report their location data to the database manager, which processes and saves it. The database manager can be hosted on any machine but should be close to the database and UAV Manager to minimize communication latency.

UAV Manager manages connections to UAVs, identifying each by type, ID, equipment, and battery level. It handles UAV operations, translating user commands into UAV-compatible instructions. As a key module, it supports UAV swarm functionality and interacts with nearly all system components.

Task Manager, located at the ground control station, makes UAV and multi-UAV cooperation algorithms accessible through graphical user interfaces. It provides algorithms as services and supports extension without system disruption. Algorithms selected by users receive data from the UAV Manager and other system components, execute at the ground station, and are translated into commands for the UAVs.

The developed multi-UAV platform is designed to host multiple UAVs, demonstrated here with three UAVs, and supports the integration of all SESAME EDDI technologies. As illustrated in Figure 4, the multi-UAV platform coordinates these three UAVs as they run the SAR algorithm, scanning the designated area (represented by the red, light red, and green lines) and searching for people, indicated by red dots. This collaborative scanning approach allows for thorough coverage and efficient detection in SAR missions.

The three images on the right side of Figure 4 display real-time video footage captured by the onboard cameras of each UAV, providing critical visual feedback that can assist operators in making timely decisions. Additionally, the UAV status information, including location and operational parameters, is shown in blue boxes, which allows for easy monitoring of each UAV's current state and performance.

The output from the selected SESAME algorithms, crucial for enhancing safety, reliability, and real-time decision-making, is presented in the red box within 4. This output showcases the active SESAME technologies impact on mission-critical operations. By using these integrated SESAME EDDI components, the platform not only increases mission success rates but also improves the resilience and adaptability of UAV operations in dynamic and challenging environments.

B. Experimental Setup

The testing environment for multi-UAV functionalities includes real-time simulations and field deployments using DJI Assistant 2 and Gazebo. DJI Assistant 2, compatible with DJI UAVs, allows users to practice flying, set home locations, adjust wind speed, collect flight data, and calibrate UAVs while providing real-time status updates. The multi-UAV platform connects with DJI UAVs through a custom Android app using the DJI mobile SDK and RF link for command transmission.

To evaluate SESAME technologies (SafeDrones, SafeML, DeepKnowledge, Security EDDI, and ConSerts), they were integrated into a three multi-UAV system controlled by the multi-UAV Control Platform. The UAVs gathered and processed real-time data for SAR operations. DJI Matrice 300 RTK UAVs, equipped with sensors and NVIDIA Jetson Xavier NX for autonomous mapping, were used. Each UAV had cameras, temperature, wind, and motion sensors for comprehensive functionality.

V. Results

A. Safety EDDI Results

To evaluate safety and reliability, we assessed the probability of failure in a scenario where the battery of one UAV out of three became faulty due to high temperature, causing a sharp drop from 80% to 40% at the 250th second (see Figure 5). It was assumed that the UAV's mission would be completed around the 510th second.

In the scenario without SESAME technologies (red line), the UAV immediately ceased its mission upon detecting the battery drop and returned to base for replacement, estimated to take 60 seconds. In contrast, with SESAME technologies (blue line), the UAV continued its mission until reaching a predefined failure probability threshold (0.9), completing the mission around the 510th second.

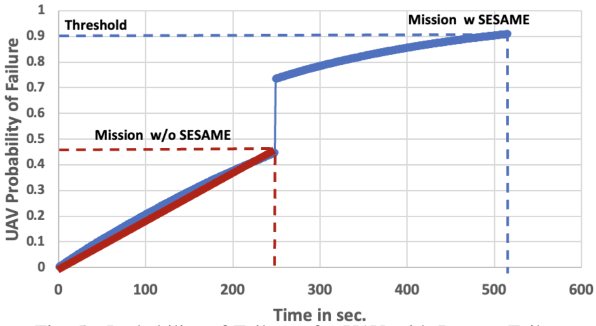

Fig. 5. Probability of Failure of a UAV with Battery Failure

Fig. 6. UAV area mapping mission with and without spoofing attack

Figure 5 illustrates the probability of failure over time for both scenarios. With SESAME technologies, the UAV sustained its mission, enhancing system availability and reliability. By the 510th second, the failure threshold was reached, initiating an emergency landing—though in this case, the mission was already complete. Using SESAME technologies maintained availability at approximately 91%, compared to 80% without SESAME, resulting in an 11% improvement in mission completion time.

B. Search and Rescue Accuracy Results

SAR algorithms in UAVs are essential for accurately locating and assisting people during emergencies. These algorithms must be highly accurate to ensure timely and effective operations. High precision enables UAVs to identify and distinguish between objects and people, even in complex and unpredictable environments, thereby maximizing mission success rates.

In this scenario, we demonstrate the importance of incorporating uncertainty values to enhance SAR accuracy. An uncertainty threshold of 90% is assumed. When the UAV operates at a higher altitude, the uncertainty levels from the output of SafeML, DeepKnowledge, and SINADRA exceed 90%. Consequently, it is determined that the UAV should descend to a lower altitude to increase SAR accuracy. Upon descending, the SAR uncertainty decreases to approximately 75%, which increases the algorithm's accuracy to 99.8%. Without SESAME technologies, these uncertainty levels are not addressed, and such high accuracy cannot be achieved.

C. Spoofing Detection and Mitigation Results

These results demonstrate the detection and mitigation of a security attack using SESAME technologies. The cybersecurity attack analyzed in this case is a ROS (Robot Operating System) message spoofing attack. In this scenario falsified data are sent to manipulate the UAVs area mapping system. Figure 6 shows how spoofing attack can affect area mapping procedure by showing the deviation of the trajectory of a UAV under attack (red color). Blue color in Figure 6 indicates the correct trajectory of a UAV with no spoofing attack. When SESAME technologies were used, spoofing attack was detected immediately by the SecurityEDDI and then the ConSerts triggered Collaborative Localization to safely land the UAV.

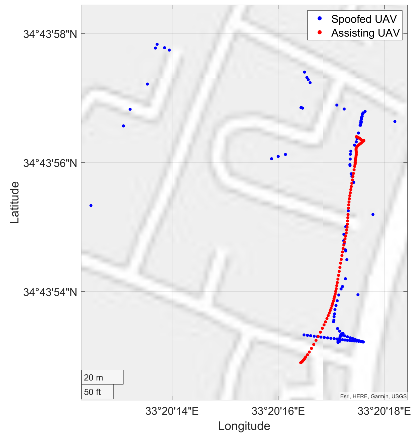

Fig. 7. Collaborative Localization showing how the spoofed UAV collaborated with the assisting UAV to safe land for further investigation

Figure 7 illustrates the spoofed UAV (shown in blue) and the assisting UAV (shown in red), which collaborate to coordinate the safe landing, in a high precision location, of the UAV under attack for further investigation. It is important to note here that the spoofed UAV is operating without any GPS signal.

VI. Conclusions

This paper highlights the advancements brought by SESAME technologies in enhancing reliability, safety, and security of multi-UAV systems, specifically in SAR operations. The integration of SESAME technologies enables UAVs to maintain effective operation even under challenging conditions. Key SESAME components, such as the ConSerts framework, collaborative localization, spoofing detection, and runtime safety assessment, strengthen system performance and ensure safe and secure mission success. The findings support the adoption of these technologies for robust and dependable UAV deployments. This work provides a clear motivation for further refinement of these technologies in diverse operational scenarios.

Acknowledgment

This work is supported by the SESAME H2020 Project under Grant Agreement 101017258 (January 2021- December 2023), by the European Union's Horizon 2020 Research and Innovation Programme under Grant Agreement No 739551 (KIOS CoE - TEAMING), by the Government of the Republic of Cyprus through the Cyprus Deputy Ministry of Research, Innovation, and Digital Policy and by the European Union's Erasmus+ Programme under Grant Agreement No 000142578 (PREVENT).

Code Availability

Regarding the research reproducibility, code and functions supporting this paper are published online at GitHub. For SESAME H2020 Project: https://github.com/sesame-project.

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