Autonomous Drones to Ensure Safety in Transport: Concept and Implementations

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***Abstract*—Transport infrastructures require continuous and efficient inspection techniques to ensure their safety. Drones are one of the latest technologies that can be used to get a deep picture of the infrastructure. However, inspecting large infrastructures such as railways and bridges demand smart drone solutions that operate cooperatively and recharge autonomously while flying in a controlled framework. In this paper, we present the concept of the Horizon 2020 project Drones4Safety and its drone ecosystem for intelligent and autonomous inspection of linear infrastructures such as railways and bridges and discuss its integration with the U-Space.**

***Keywords*—Autonomous operations, Self-recharging, Inspection, AI, Swarming, Cloud services.**

I. Introduction

The Drones4Safety (D4S) project is 3-years Horizon 2020 project started in June 2020 and aims to increase the safety of the European civil transport system by developing a system of autonomous, self-charging, and cooperative drones to inspect a big portion of transportation infrastructures in a continuous operation. D4S solutions utilize the existing energized infrastructures as overhead power or rail lines to charge its drones to operate for a longer time. It gets information about the applicable transport infrastructure to be inspected from open maps and satellite data and forwards that information to its drones to conduct their autonomous and collaborative inspection missions.

The D4S conceptual view is depicted in Fig. 1 and shows a set of drones that have a self-charging capability to harvest energy from overhead power line cables (transmission lines/railway catenary lines). The drones work autonomously in a swarm and apply sensor fusion and onboard signal processing techniques to fly, inspect, and recharge. The collected images are checked using advanced AI algorithms that are trained against faults in the transportation infrastructure (railways/bridges) data. The drones are connected through the cloud to the end-user in which inspection services such as mission control, fault detection reports, and swarm fleet management are provided.

The D4S project's main objectives are:

- providing an autonomous drone platform for a cooperative drone operation for inspections and recharging,

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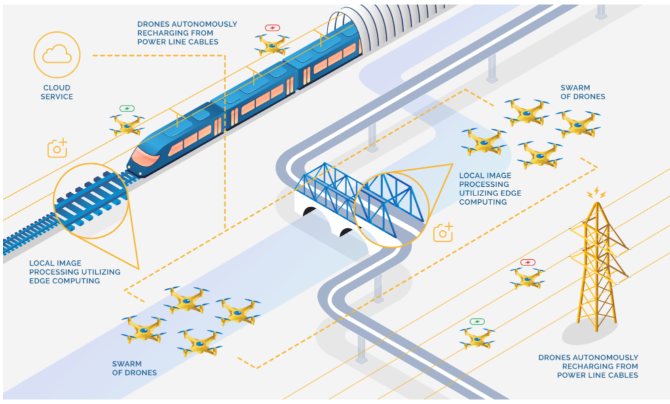

Figure 1. Conceptual view of the Drones4Safety project.

- developing a solution for harvesting energy from AC and DC overhead lines for continuous drone operations,
- increasing inspection efficiency by using AI algorithms for fault detection,
- building a cloud system for autonomous navigation and mission control.

These features will enable drones to inspect linear railway and bridge infrastructures across the EU member states while benefiting from the recommendations by the European Union Aviation Safety Agency (EASA), highlighted in [1], for having common European rules on drones to ensure safe, secure, and sustainable operations.

Our analysis predicts that the D4S system can inspect the whole European electrical railway system and a big portion of the European bridges that are near the high-voltage and/or railway cables. Table I shows the number of bridges (also in %) that can be inspected by the D4S project in the EU as a whole and in Italy as a target country, chosen due to the national demand that was raised after the Genova bridge collapse in August 2018. Considering normal drones can fly for around 20 km per charge, thus, a drone can reach a part of an infrastructure, inspect it, and go back to recharge.

Nearest powerlines	1km	3km	7km
Bridges in EU	228,805 (15.2%)	1,070,304 (71.1%)	1,371,241 (91.1%)
Bridges in Italy	14,946 (38.7%)	28,557 (73.9%)	36,498 (94.5%)

TABLE I. Number of bridges that can be inspected

II. Hardware/Software

The drone system for autonomous recharging from powerlines is utilizing data from a multitude of sensors, including

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mmWave, camera, and magnetometer sensors. The sensory data is fused onboard to accurately detect and estimate the 3D pose of the powerline. Fig. 2 shows the full hardware software architecture of the D4S drones. The following sections explain in details its sub-components.

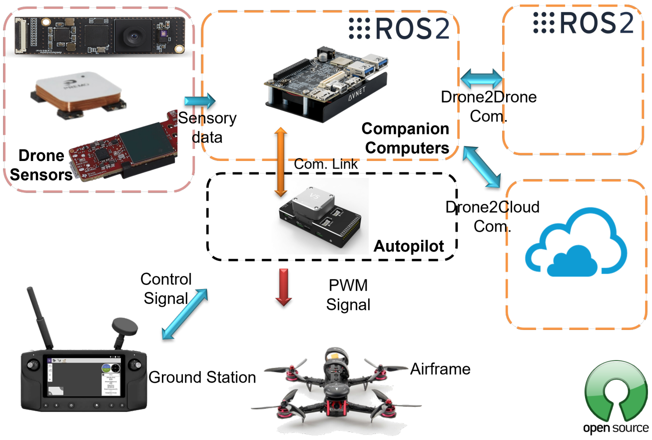

Figure 2. Hardware/Software architecture of the D4S project drones

A. Onboard Computing

The onboard processing is utilizing the cutting-edge Zynq UltraScale+ Multiprocessor System on a Chip (MPSoC) series from Xilinx which combined FPGA fabric with a CPU. This enables the designer to run non-real-time critical software on the Application Processing Unit (APU) using an Operating System (OS) such as Linux; to design real-time critical software for the Real-time Processing Unit (RPU) to run bare-metal or on a real-time OS, and finally to design any application-specific hardware acceleration and a custom logic circuit for the FPGA chip. Additionally, the MPSoC uses the AMBA AXI open data communication standard for intra-chip communication. This enables the designer to build an FPGA circuit that maps into the memory of the CPU for easy integration of implemented hardware acceleration cores in the application AXI.

The onboard computer plans a flight path in real-time to guide the drone to the desired recharge point. Read more about the drone onboard computer in [2], [3].

B. Software Layers

The drone software architecture is composed of a network of modules that support autonomous inspection services in both practical environments and simulated platforms [4]. The architecture divides a High-level Controller (HC) and a Low-level Controller (LC) deployed on separate hardware blocks. The LC deals with standard flight control by using the PX4 autopilot flight stack. The HC offers autonomous flight and inspection services based on the second generation of the open-source Robot Operating System (ROS) middleware, ROS 2 [5]. ROS 2 was redesigned from the ground up to solve many challenges of modern robotics. ROS 2 utilizes the open standard for communications, Data Distribution Service (DDS), to obtain best-in-class security, embedded and real-time support, multi-robot communication, and operations in non-ideal networking environments for building reliable robotics systems.

The drone software architecture integrates ROS 2 nodes into the drone system making it easier to focus on application-specific software development.

C. Powerline Detection System

The powerline detection system relies on mmWave radar measurements and RGB camera images. The sensors are mounted on the drone such that they look upwards toward the overhead cables. The mmWave sensor returns a few points in 3D space that represent the cable's position relative to the drone. The mmWave measurements do not inform about the cable direction, therefore, the camera is used to extract directional information about the powerlines by applying a Hough-lines algorithm on its data. The algorithm is accelerated on the FPGA to speed up the perception system. Fig. 3 shows a prototype of the D4S drones. The details of the perception system and data processing are presented in [6].

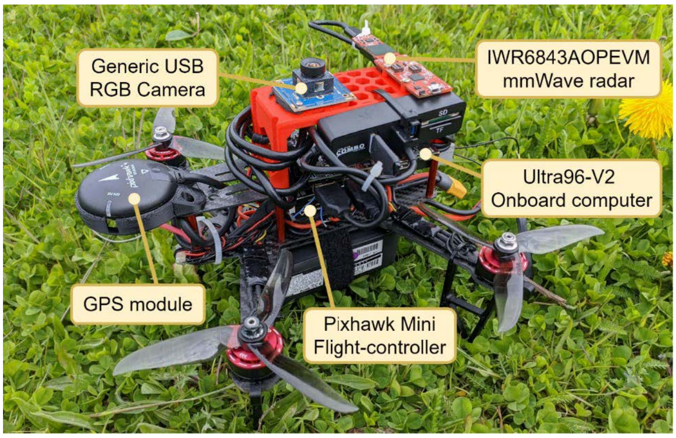

Figure 3. A prototype of the autonomous drone for cable detection

III. Swarming

Swarming concerns the coordinated operation of multiple drones to accomplish large-scale, complex missions. The benefits of swarming include improved fault tolerance, increased performance, reliability, and simplicity in design. Small and simple drones will be easier and cheaper to implement than having only one single powerful drone [7].

A. Drone Communication

Resilient and robust wireless communication is a prerequisite for an efficient swarm operation. The system architecture of the Unmanned Aerial System (UAS) segregates communication according to three distinct interfaces: Drone-to-Ground (D2G), Drone-to-Drone (D2D), and Drone-to-Cloud (D2C) communication [8]. The D2G communication requires robust, long-range wireless communication to ensure timely telemetry data from drones. The data rate is traded off with the range of the communication and radio standards such as LoRa, therefore, becoming a suitable technology choice. LoRa can support communication of up to 20 kbps and maximum distances up to 11.5 km with LoRa communication operating in the 868 MHz radio band [9]. Drones operating in swarms allow shorter-range wireless technology to be chosen for D2D communication. A higher data rate can be achieved to serve the coordination protocols, which allows for shorter latency in communication. Wireless mesh networking with WiFi is a suitable technology for the D2D communication supports data rates of several Mbps with a latency of less than 30 ms. D2C communication offers access to the mission control function running in a private cloud over the Internet. Drones may be equipped with 4G/5G mobile communication capabilities and can exchange information with cloud services through the terrestrial mobile network including a continuous upload of inspection images.

B. Algorithms for Swarming

The autonomous inspection process is supported by a set of algorithms that allow drones of the swarm to interact cooperatively. In the following, we will address essential algorithms for efficient drone swarm operation.

1) Task allocation: Task allocation concerns the assignment of a set of tasks to a set of drones in such a way that it optimizes the overall system performance subject to a set of constraints [7]. Our inspection mission is composed of an aggregate of tasks that can be allocated to drone members of the swarm. Tasks are constructed to be feasible and attainable for a single member of the swarm. A task is represented as a data structure with a start- and end-location, actions to be taken by the drone, and a specification of sensors and actuator settings. A drone will execute the allocated tasks autonomously. Several options for a task allocation algorithm exist, such as the Fair Division Problem, Optimal Assignment Problem, and Multiple Traveling Salesman Problem [7]. Our inspection mission consists of single-robot tasks. This means that each drone is capable of executing at most one task at a time and that each task requires exactly one drone.

2) Cooperative motion path planning: Motion path planning algorithms are used to generate geometric properties of a path from a start to an end-location, passing through predefined intermediate points. To control a swarm, a multi-drone motion path planning is required to generate safe trajectories respecting the constraints of the system such as keeping distances between a minimum and a maximum value to avoid collisions and still maintain the coherence of the swarm. We formulate the multi-drone motion path planning problem as a cooperative decision-making process modeled by game theory. To approach efficiency optimization for a swarm, the concept of the Generalized Nash Equilibrium Problem (GNEP) is used [10]. The computation of the equilibrium guides each drone in the swarm to calculate its control inputs subjected to the dynamic limitations of the drone and obstacles of the environment. Swarm members share the motion strategies to achieve coordination between drones. The equilibrium calculation achieves a strategy that approximates the optimal of the drone swarm, i.e., the Nash Equilibrium, at the expense of optimal strategies of individual drones. The proposed method is based on the continuous exchange of motion paths of the drones in the swarm.

3) Formation flying: Inspections of linear infrastructures such as railways and powerlines can benefit from flying the drone swarm in formations. A formation allows the simultaneous observation of a target segment from different viewpoints or with different sensors. Our approach to formation flying is based on the leader-follower scheme [11], in which the leader drone is assigned the set of inspection waypoints for the entire swarm. The leader drone takes control of disseminating waypoints to the follower drones over the D2D communication channel. Inspection tasks are executed by the drone using onboard position control. The leader drone subscribes to the position and velocity of its followers offering the opportunity to adapt the formation to the environment. Due to its simplicity, the approach does not require heavy computation and can be executed by the drone during mission execution.

4) Coordinated charging: The drone swarm implements a charging protocol to ensure the continuity of the inspection mission. Depending on the type of mission, drones charge on specified locations of overhead powerlines or at designated charging stations. Our charging schedule protocol aims to minimize the total execution time of the mission by allocating charging tasks to the individual drones of the swarm. The optimization problem is constrained by the batteries of the drones that cannot fully deplete and the charging station that can only serve one drone at a time. For each allocated task, the charging protocol determines if a drone should proceed directly with the next task, or if it should visit one of the charging locations. Furthermore, the charging scheduler decides how much time each drone must wait before charging and the duration of the charging.

C. Security of Swarms

The long-term commercial viability of autonomous inspections with drones heavily depends on the level of trust that can be provided to the end-users. Security threats to drones are typically targeted at the UAS system level and target everything employed to allow the drone to function, i.e., the hardware/software, the ground control system, and the communication. The design of the drone swarm must ensure the protection of information generated, the resources and services provided, the compatibility with worldwide security standards, the interoperability with well-proven secure algorithms, protocols, and practices, and the protection of the system against theft and malicious use.

In [12], we presented an assessment of the security vulnerabilities of the D4S drone system based on the STRIDE threat methodology. The STRIDE methodology considers threats against a system from a balanced set of viewpoints. It concerns Spoofing, Tampering, Repudiation, Information disclosure, Denial of Service (DoS), and Elevation of privilege attacks. The landscape for security threats to the UAS not only embrace well-known threats from digital information systems but is also hampered by drones with limited resources operating in a hostile environment. The most severe threats to the drone swarm concern spoofing and DoS attacks. Furthermore, we find that tamper-evident logging, intrusion detection, and drone safety protocols are important techniques to ensure trust in the autonomous operation of drone swarms for inspections.

IV. Cloud Service

The computational and storage resources available onboard the autonomous drone are severely limited in at least two ways. First, requirements regarding the weight and robustness of the drone imply that the onboard computer is only suitable for rather light processing and does not scale to the complex machine learning and other computational models needed for fault detection, 3D reconstruction, and similar tasks. Second, any onboard processing affects the battery life and, thereby, the flight time of the autonomous drone. Furthermore, as the drone operates autonomously, it is a requirement that the drone operator can control and monitor the drone remotely. To this end, the drone needs a constant (or near-constant) communication link to a control and monitoring system. This communication link can be exploited to move as much as possible of the computational and storage requirements to a cloud system, where practically unlimited resources can be made available [13].

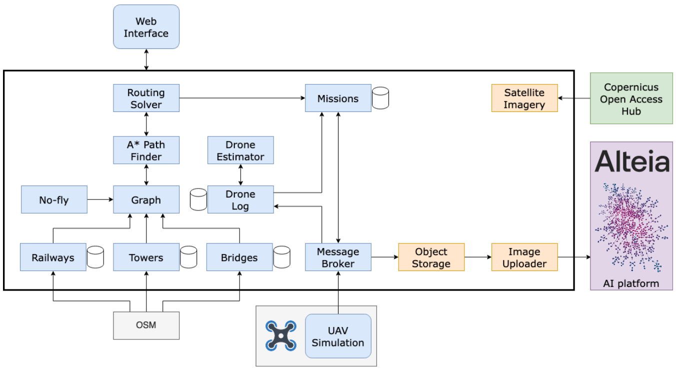

Figure 4. The architecture of the Cloud Service

Fig. 4 provides an overview of the microservices that constitute the backend of the architecture of our cloud service. The drone operator interacts with the system using the web interface. The web interface communicates with the backend by sending requests and serving responses to the user. It is implemented and deployed as a microservice. The operator selects inspection targets on the web interface, which creates a request to the Missions service. The request contains target locations. The mission service has drone locations stored and, with received target locations, sends the request to the Routing Solver. The Routing Solver uses the A* Pathfinder service to determine the order of visiting all the targets. The A* Pathfinder, in turn, requests the graph created from data stored in Towers, Railways, Bridges, and No-fly services to determine the shortest path for each combination of target location and drone location. The calculated routes are stored in the Missions service, visualized on the web interface, and sent to the drone (simulated or real) through the Message Broker.

While the mission is in progress, the Message Broker sends drone telemetry data to the Drone Log service, where the data is stored. The Drone Estimator service uses telemetry data to estimate the drone location in periods when drones are not reporting to the cloud. Estimation data is stored in the Drone Log service database for mission simulation after the mission finishes. The Message Broker updates the Missions service database with inspection results. Images from the drones are stored in the Object Storage, with the transfer handled through the Message Broker. The Satellite Imagery service accesses satellite data from the Copernicus Open Access Hub. The Image Uploader uploads images to the Alteia AI platform where the images are analyzed using deep learning techniques for fault detection.

V. Energy Harvesting

Overhead power lines and railway catenary lines were intended to serve as an energy source for the recharge of the drone's battery. When the drone reaches a low battery status during its inspection flight, it approaches the power line and grasps it to induce current to charge its battery. Due to the strongly different boundary conditions, such as AC and DC currents as well as the different voltage levels low voltage, medium voltage, and high voltage, different concepts are required. As part of the D4S project, concepts for AC and DC lines were developed and evaluated with demonstrators.

A. *Energy Harvester for AC lines*

In [14], [15], the concept of the drone's recharging at AC lines was shown by using an inductive harvester. The harvesting device consists of a soft magnetic transformer core made of electrical steel. Ideally, it fits as close as possible to the primary current cable. To harvest energy from the magnetic field, a secondary winding on the transformer core is needed to generate the induced voltage. The AC voltage of the transformer has to be rectified and buffered into a DC voltage within the first stage of the harvester electronics. A protection circuit limits the input voltage to a defined level to protect itself and the following stages from over-voltages. These happen when the input power is higher than the usable output power, e.g. in the case of a line short event of several kA or when the battery is fully charged. In normal operation, the charging currents can be up to 10 A from overhead powerlines and up to 5 A for railway applications, depending on the line's primary current.

B. *Energy Harvester for DC lines*

Another option is the use of DC railway lines for re-charging. The principle of harvesting is the direct contact be-tween the high-voltage DC line and the ground of the railway catenary system. A challenge here is the handling of the high-voltage with simultaneous strong voltage variations due to the changing loads caused by trains. The harvester electronics were realized with a high-voltage DC/DC buck converter with direct down-conversion. In direct down-conversion, the voltage is transformed into a low-voltage, as in a switched-mode power supply. It was decided to develop a two-stage converter. The first stage converts the voltage from 3 kV to 300 V and the second stage converts from 300 V to the required voltage of the charge controller of 30 V. This makes it easy to adapt the solution to the common voltages between 700 V and 3 kV in the first stage and a readily available component was used as the second stage.

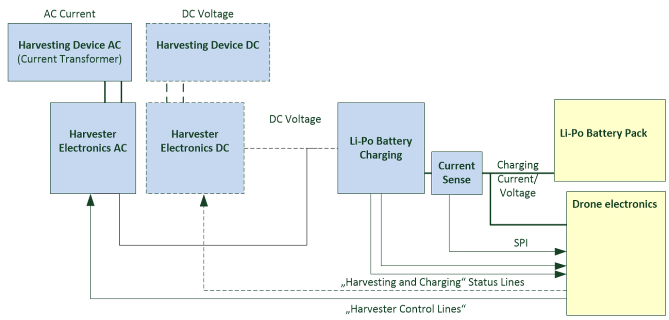

Figure 5. Block diagram of the harvester electronics

Fig. 5 shows an overview of the stages of the harvester electronics. For AC and DC harvesting, the harvesting device and the electronics differ, the lithium-Polymer battery charging part basically can be the same. For AC and/or DC harvesting, the harvester currents are expected to differ, thus different part choices for the highest possible efficiency make sense.

The high-voltage DC/DC converter is designed to deliver a maximum of 150 W. This value is a trade-off to stay in a reasonable range for heat dissipation, size, and weight, Fig. 6 shows the PCB board with heat sinks. Therefore, the charging current has been limited to approx. 6 A. The charger applies the CC/CV (constant current/constant voltage) mode which is suitable for LiPo batteries. In this mode, the battery is charged with a constant voltage up to a certain threshold. After the battery voltage reaches this threshold, the charger switches to a constant voltage which accordingly reduces the charging current.

The test and characterization of high-voltage DC/DC-converter was conducted in the high-voltage lab of the Fraunhofer Institute. The controller of the first stage regulates the output to 300 V and the second stage starts about ten milliseconds after a stable input voltage above 200 V. The dynamic characteristics was tested by a variable load, presented by switched resistors.

VI. Artificial Intelligence

Analyzing thousands of pictures collected by a drone is a challenge for inspectors, especially if the task is carried out manually. Fortunately, automating asset and anomaly detection on pictures can be supported by AI-based analytics.

Figure 6. The realisation of the DC circuitry of the harvester electronics

A. Fault Detection techniques

The task of detecting objects of interest from images is a well-known problem in the computer vision community. In the last few years, the state of the art of such tasks is deep neural networks [16]–[18]: the first distinction between different types of AI tasks is based on how the model will produce its outputs in terms of bounding boxes, polygons or segmentation masks. A second distinction is based on the type of learning approach: *Supervised learning* is a machine learning approach that's defined by its use of labeled data sets. These data sets are designed to train or "supervise" algorithms into classifying data or predicting outcomes accurately. Using labeled inputs and outputs, the model can measure its accuracy and learn over time. *Unsupervised learning* uses machine learning algorithms to analyze and cluster unlabeled data sets. These algorithms discover hidden patterns in data without the need for human intervention (hence, they are "unsupervised"). Unsupervised learning models are used for three main tasks: clustering, association, and dimensional reductions.

B. Training Data

For supervised learning, public and private data sets were used both for bridges and railways with hundreds of pictures. For unsupervised learning, the bridge use case was mainly investigated with the purpose of detecting with auto encoder based models the presence of cracks. However, a supervised learning approach requires more than one thousand examples for each anomaly class to be effective. This required a boost for the project's synthetic data.

1) Synthetic Datasets: Fig. 7 shows an example of bridges with segmented assets, Fig. 8 shows a synthetic bridge with rendering applied and Fig. 9 shows an example of railways with rendering in a sunny environment [left] and with segmented assets [right] have the advantage of being able to generate as many training examples as possible if the virtual environment created is large enough. Many works suggest that even if the images generated with this approach are not as photo-realistic as an image on the field, the results can be good enough to bootstrap an initial model that can work well for production use. Some successful approaches in [19], [20] have been reported in robotics and perception for general perception tasks. The transport industry has also started to adopt this method in the context of autonomous driving.

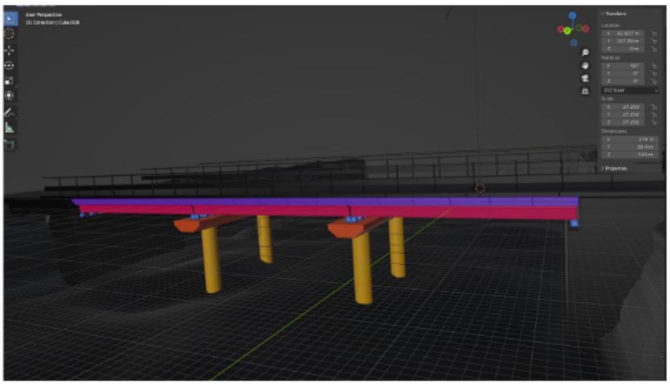

Figure 7. Bridge synthetic model with segmented assets

Figure 8. Bridge synthetic model with rendering

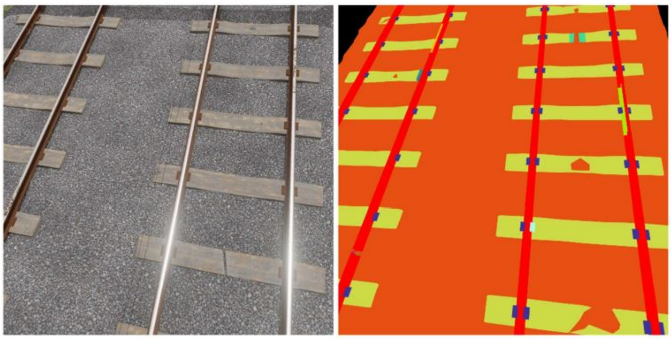

Figure 9. Railways synthetic model

To create the synthetic, a "simulated environment" approach was used from [21]. This approach consists in recreating the geometry of a scene of interest for the problem in 3D engine software. Different tools like Blender, offer capabilities that permit the modeling of any complex 3D object like bridges, railways, etc. and also to apply textures and material properties to such objects in order to make them as photo-realistic as possible.

2) Semantic Segmentation: Once the scene has been built, the user can also choose the luminosity conditions, the meteorological conditions, and the camera parameters in order to extract images from a rendering procedure. The other great advantage of such an environment is that the user can also have a semantic segmentation map of the various objects of the scene without any need for human intervention since the rendering process can directly output such maps. The annotations created in such a way have also the advantage to be pixel-perfect and do not present all the uncertainties and artifacts that a human annotation process usually has. Different types of scenes were produced for bridges, starting from the three most common bridge structures, namely Girder, Arch, and Suspension bridges.

In addition, three different types of scenes were produced covering the common 2 types of railways; namely, standard and high-speed rails.

C. AI Model

The chosen AI model is based on an instance segmentation task, in which the model will output the polygon that describes the object contours for each of the elements and anomalies in the images. The choice produced 2 main benefits:

1) avoiding problems of superposing bounding boxes. In this case detection of objects that have a lot of superposition can be eliminated by the model itself due to a step called "non max suppression" which is ubiquitous in all the various detection networks.
2) being able to view multiple defects in the same zone. In this scenario, the end user is interested in having the information on the presence and the position of all the various anomalies.

The deep learning model used to solve the defect detection problem is called "Mask R-CNN", a Convolutional Neural Network (CNN). Mask R-CNN was developed on top of Faster R-CNN, a Region-Based CNN. This architecture is considered the state of the art in this kind of task and it is especially well known for its robustness to various data sets and hyperparameters.

Results can be summarized as follows:

1) the developed algorithm (for both use cases) is better performing when applied on mixed data sets (rather than on pure real data sets) as a consequence of the input quality of pure real data sets.
2) the recall is much higher than precision, showing a tendency to detect more defects than reality (false positives proposed by the algorithm).

This is not an issue as a filter can be later applied to remove the false positives.

Within the context of the D4S project, Alteia has proposed a detailed recipe to use an open source software to create artificial data sets for supervised anomaly detection problems. Even starting from a common baseline, a CNN can perform well enough on real data to be considered useful in the context of infrastructure inspections. Worth noting, the problem related to the drop in performance when switching from synthetic data to real data should be further investigated.

VII. Use Cases

The D4S functionalities are validated in a cluster of different Use Cases (UCs) including real railway/bridge scenarios and controlled environments (indoor/outdoor test facility). Safety, operative limitations and regulatory restrictions are some of the main reasons preventing the testing of the D4S system as a whole in a single real UC scenario.

A. Bridge Use Case

Different sites, located in Italy, have been analyzed, to find possible suitable locations as the best option from multiple points of view (safety, number of testable functionalities, authorization processes, access to the area, presence of obstacles, etc.). Unused reinforced concrete (RC) bridges/viaducts overpassing no trafficked roads (e.g., river or valley) in easy-to-access areas without strong regulatory restrictions have been the preferred options. The bridge UCs are focused on the workflow of inspection activities supposed to be repeated several times on the same structure (according to a defined routine maintenance plan) and for which having an autonomous process is an important benefit. In this context, the 3D model reconstruction is an input available data coming from an activity carried out once per structure. In Fig. 10 the main steps of the "ideal" process are shown: once the structure is known, inspection paths are planned and executed thanks to the Drone Inspection as a Service (DIaaS) platform, eventually recharging batteries or safe landing if needed. Once collected, images are sent to the Alteia platform which processes all the acquired images by means of a supervised algorithm and reports damages (type and location) as input to the structural assessment performed by the EUCentre toolbox, whose output is intended to be a support to decisions for the infrastructure owner, in the case damages are found to possibly jeopardize the structural performance of the bridge.

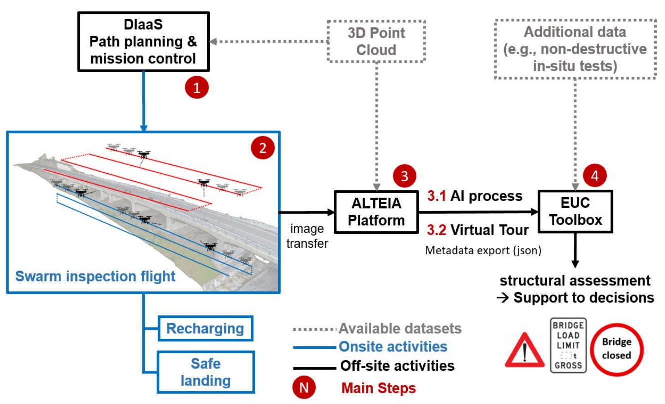

Figure 10. Inspection workflow on bridges

The main designed bridge UCs are basically two: the former consists of a real in-situ deployment of the swarm system, in which steps 1 to 3 are carried out, while the latter will consist of steps 1-2 carried out within a simulated environment (due to safety reasons) and steps 3-4 actually carried out. The latter case has been necessary because the former bridge does not show any significant visible damage. The first UC is conducted on a long RC viaduct belonging to an occasionally used railway route. The viaduct is a reinforced concrete wall piers structure with 144 bays for a total length of about 3.7 km and a maximum high of about 20 m. The missions are focused on a portion consisting of four 25 m bays, for a total length of about 100 m, a maximum height of about 10 m (with a pier height of about 7 m), and a transversal dimension of the deck of about 6 m. This portion of the viaduct is inserted in an easy-to-access, sparsely populated area.

The drone swarm system used during this mission consists of two multirotors with Maximum Take-Off Mass (MTOM) under 2 kg, with one front camera, one downward camera, one front stereo-camera, one depth camera and onboard Inertial Measurement Unit (IMU). Each platform features a number of risk mitigation measures such as geofencing, recovery functions, fight terminator, and obstacle avoidance sensors. For the purpose of the case study, particular safety arrangements are taken in order to keep the risk of the operation basically equivalent to the one of the A2 open category, according to the current National Aviation Authority (NAA) regulation [22]. Such arrangements, which are schematically shown in Fig. 11, do not impair the testing of the system functionality. The swarm is controlled by the solely "swarm pilot", driving the operation by means of a Ground Control Station (GCS), and two safety "Backup pilots" able to take over the control of each drone, in case of need. The flight mode of the swarm system can be considered an "automatic operation" according to the European Regulation definitions [23]. In particular, two different flight modes can be run: "Standard automatic" (the drone follows the path plan input by the "Swarm Pilot") and "Position control" (the drone hovers in the air, this mode can be activated at any time by any of the backup pilots). Accord-

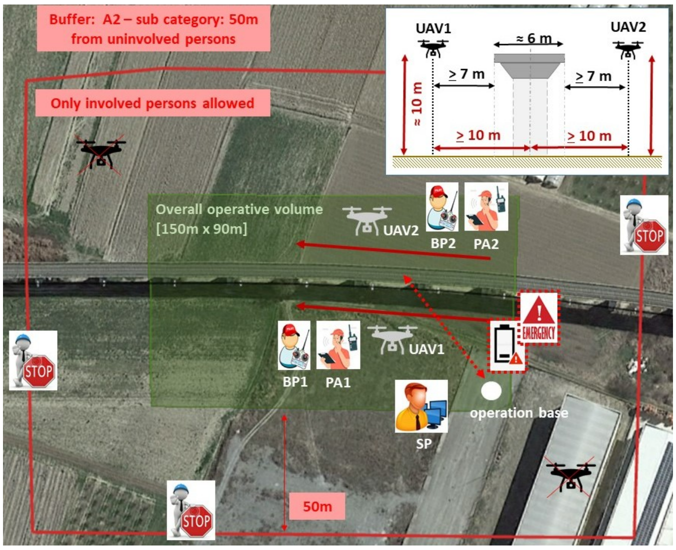

Figure 11. Asti Bridge UC: Mission scheme

ing to the safety analyses, all the flights planned are carried out in compliance with daytime, Visual Line Of Sight (VLOS) conditions, 15 m above ground maximum flight height, within a controlled area, in a sparsely populated region, without traffic overpassing the viaduct, and in uncontrolled airspace. In order to guarantee a proper horizontal separation, the two drone operation volumes do not interfere one each other, as shown in Fig. 11. Concerning the duration of the operations, 4 to 6 flights of about 15 minutes are planned. During the mission, the following main functionalities are supposed to be validated: simultaneous swarm inspection flights (planned from the previously acquired 3D point cloud model), Artificial Intelligence (AI) detection algorithm especially of elements, simulation of a flight to/from recharge point and/or of battery recharge by at least one of the drone of the swarm.

B. Railway Use Case

As for the bridges, several test sites for railway UCs have been selected to cover the different types of missions, i.e.:

- damages to the electric traction overhead contact lines,
- tracks and roadbed deformation,
- obstacles on tracks,
- 3D map generation,
- target objects inventory creation.

After a proper analysis, which took also into account the electrification type (AC/DC), the restrictions to flying, the accessibility of the area, the safety implications (both from the railway and the aviation point of view), coverage of the UC, regulatory and authorization processes, presence of damages, etc., several flight missions have been conducted on both conventional (see Fig. 12) and high-speed lines (see Fig. 13) using standard drones in order to create maps and to acquire sample datasets of images and, possibly, damages, to feed the AI algorithms. The multirotor drones used for these missions had an MTOM under 2 kg, and were equipped with an RGB camera for front and downward acquisitions.

Figure 12. Conventional railway use case

The flight operations have been conducted under the specific category, as defined by the current NAA regulation [22], and, in particular, under the prescriptions of the Italian Standard Scenario (IT-STS) for Critical Operations IT-STS-02 [24].

Figure 13. High-speed railway use cse

VIII. Integration with the U-Space services

In recent years, the need for traffic management focused on UAS emerged in many parts of the world. This UAS traffic management system (UTM) would ensure the safe operations of a large number of drones at low-altitude (especially in urban areas). As traditional air traffic management (ATM) ensures the safety of aircraft operations at high-altitude, so does UTM at a lower altitude. The Commission mandated the SESAR JU to lead the development of a UTM concept for Europe, called U-Space. The concept of operations for U-Space has been initiated and is currently maintained by the Projects CORUS and CORUS-XUAM [25]. It consists of a set of services enabling complex drone operations in all types of operational environments. The progressive deployment of U-space is linked to the increasing availability of blocks of services and enabling technologies. Over time, U-space services will evolve as the level of automation of the drone increases, and advanced forms of interaction with the environment are enabled (including manned and unmanned aircraft) mainly through digital information and data exchange. The U-space services defined so far are here listed in Fig. 14.

- **U1: U-space foundation services** covering e-registration, e-identification, and geofencing.
- **U2: U-space initial services** for drone operations management, including flight planning, flight approval, tracking, and interfacing with conventional air traffic control.
- **U3: U-space advanced services** supporting more complex operations in dense areas such as assistance for conflict detection, and automated detect and avoid functionalities.
- **U4: U-space full services**, offering very high levels of automation, connectivity and digitization for both the drone and the U-space system.

The D4S project has two main streams of connection with the U-Space roadmap: on one side, the project takes the U-Space services as an input for the development of the D4S

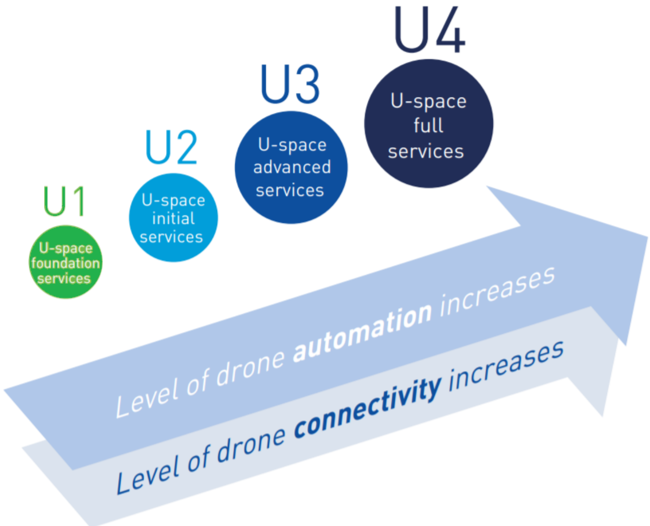

Figure 14. U-Space services from U1 to U4

concept of operations and use cases (e.g. e-registration, e-identification, and geofencing are considered both prerequisites and enablers for the execution of the use cases); on the other side, the project is collecting and putting together best practices and recommendations that may feed the development of the most advanced levels of services for the U-Space (e.g. the drone communication, the algorithms for swarming and the security aspects depicted in section III of this paper can offer recommendations to the U4 services). The final reports of the project will contain a structured and detailed collection of the evidences produced by Drones4Safety that will be shared with other projects, working groups, and initiatives dealing with the development and deployment of U-Space services.

Conclusion

The paper has presented the concept of the H2020 Drones4Safety project for transport infrastructure inspection using autonomous drones. The developed technologies in drone design, energy harvesting, AI, and drone swarms have been presented and discussed.

Finally, the paper briefly introduces the railway and bridge use cases design for the validation of the main D4S functionalities (according to the current level of definition) and the integration with U-Space services.

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