Leveraging Multimodal Synthetic- and Real-sensor Data to Enable Safe Flight Operations in Fair and Degraded Visual Environment

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ABSTRACT

Fully autonomous flight for certifiable commercial flying vehicles is currently far in time. We present an approach to develop advanced environmental perception functions to improve external situational awareness of pilots and autonomous flight mission management systems, to enhance safety, increase survivability and to expand the envelope of potential operations achievable by the vehicles. Our approach is based on a simulation environment capable of simulating different sensor modalities (such as visible camera, LiDAR, and RADAR) validated with real-world sensor data. We also describe the requirements that such environment must have to prove its usefulness towards the goal of autonomous-flight function development.

1.0 INTRODUCTION

A possibility to achieve autonomous flight on flying vehicles and especially helicopters is to imitate what is done by the majority of the players in the automotive sector [1]. Indeed, autonomous cars often rely on a set of diverse sensors (e.g., visible cameras, LiDARs, and RADARs) and their corresponding algorithms (e.g., multimodal sensor fusion) [2]. In the case of helicopters and other flying machines, especially if certified for civil or commercial use, the enabling of autonomous flight will be even more gradual than in the automotive sector. This aspect is in line with the technology and international regulation development. In commercial helicopters, about 40% of total accidents between 2009 and 2018 were due to low situational awareness [3]. More specifically, prior to the former analysis, EASA reported that quite a number of rotorcraft accidents occurred due to a degraded visual environment (DVE) scenario [4]. This problem occurs with high correlation with lightweight, single-engine piston-powered rotorcrafts with a relatively inexperienced pilot. Therefore, we believe that a first step towards enabling autonomous flight on helicopters could be the enhancement of the environmental situational awareness of the pilots. Unfortunately, testing and integration of different sensors on helicopters suffers of two major problems:

1) It is very costly both financially (1 hour of flight of a prototype helicopter can cost more than 5 kEUR) and environmentally (1 hour of helicopter flight can generate more than 850Kg of CO2 [5])

2) It is not possible to cover edge (when an operating parameter is at extreme level) and corner (when parameters are outside normal operating conditions) cases adequately. According to our pilots, often corner cases are compromising their flight and putting the crew and machine at risk (e.g., takeoff

and landing in brown- and white-out conditions).

In this work, we present an approach that mitigates these two problems by relying on a high-fidelity physics-based sensor simulation environment (see **Figure 1**).

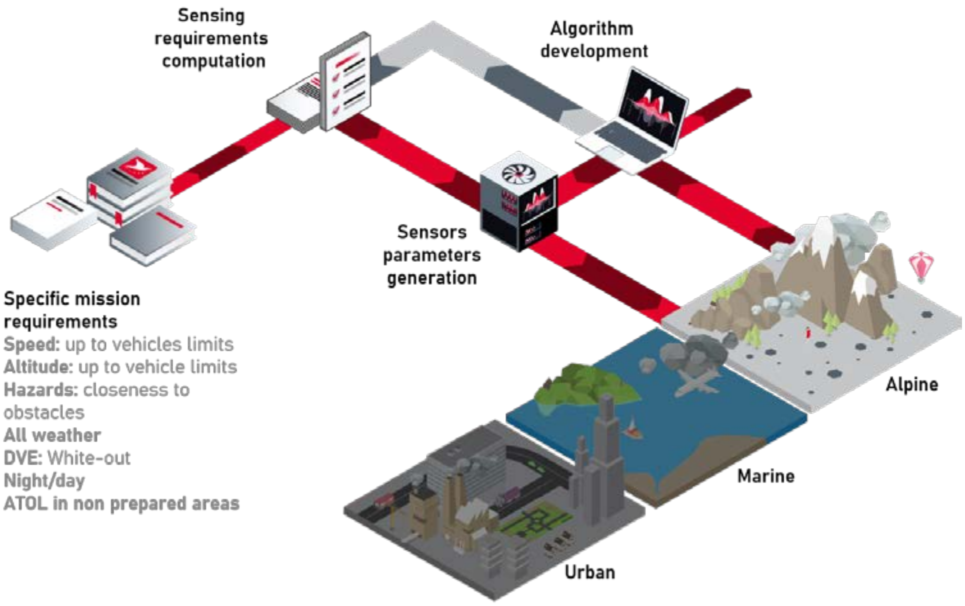

Figure 1: The workflow of our approach - The first step is the identification of the specific mission requirements depending on the mission to be tackled (e.g., search and rescue operation in a mountainous environment). From the mission requirements, the next step is the definition of the sensing requirements leading to the generation of the sensor parameters (e.g., camera/LiDAR/RADAR field of view and resolution). The sensors are deployed in an environment fitting the mission requirement (e.g., alpine) and the specific algorithm development begins.

2.0 OUR APPROACH

In the last decade, we have witnessed much effort in the development of photorealistic simulators [6]–[8]. However, only few of them are capable of simulating with high fidelity the behaviour of a real-world camera, focusing more on reproducing what humans consider realistic. Moreover, they typically lack other sensor modalities, such as sensors operating at a shorter wavelength (e.g., infrared cameras, RADARs). To the best of our knowledge, almost none of them are capable of high-fidelity physics-based simulation of sensors. This gap is even more prominent considering degraded visual environment scenarios simulation. Nonetheless, even if in simplified simulation environments, several works have highlighted how by increasing visual cues to pilots can improve their situational awareness [9], [10]. As we mentioned in Section 1.0, our approach leverages a synthetic simulation environment capable of simulating several sensor modalities such as visible cameras, LiDARs, and FMCW RADARs. Regarding the latter, we noticed that they attracted a lot of attention in the last years. This interest is certainly driven by the automotive sector and some datasets including LiDAR, visible cameras, and RADAR are already available [11], [12]. However, being mainly tailored to the automotive sector, currently available datasets are not fully representative of the scenarios of our interest. Indeed, there is a lack of annotated data for small objects, flying objects, and highly diverse scenarios and we believe that our simulator will also help to fill this gap. In summary, the simulator allows to (i) generate annotated datasets and (ii) test autonomous-flight algorithms with different sensors in several scenarios at a lower cost compared to real-world flight tests, since it does not need flying any real helicopter (at least in a preliminary phase). **Figure 1** depicts the workflow we propose to develop our autonomous-flight algorithms. Our approach entails two building blocks:

1.0 We are currently developing a software suite able to leverage the simulator capabilities for the analysis and fusion of the output of several simulated sensors. This element will allow us to show to the pilots a type of information that they would otherwise not be able to gather (e.g., the presence of a cable outside the pilot's field of view in takeoff and landing phases). This kind of information will increase the safety of the crew and the flying vehicle.

2.0 Since the simulation environment we chose is not yet capable of high-fidelity simulation of DVE scenarios, we are planning a real-world experimental test campaign with real sensors in controlled DVE scenarios (e.g., artificial snow, fog, rain). This element will allow us to quantify the effects of DVE conditions across all the different sensor modalities. Up to our knowledge, these tests will be among the first in the aerospace sector and are similar to tests performed for example for LiDARs in the automotive sector [13]–[16]. Our ambition is to gather data from all the sensor modalities synchronized, yielding a potential advantage for civil and military next generation Leonardo platforms.

3.0 PRELIMINARY RESULTS

The work presented in this abstract is ongoing and we have currently preliminary qualitative results regarding the first point described in Section 2.0: the development of the software suite revolving around the physics-based simulator. We explored three main directions related to three sensor modalities: (1) a geometry-based LiDAR/Camera fusion (see **Figure 2**), (2) an image semantic segmentation architecture (see **Figure 3**), (3) a software to interpret the measurements of a FMCW RADAR sensor starting from raw data (see **Figure 4**).

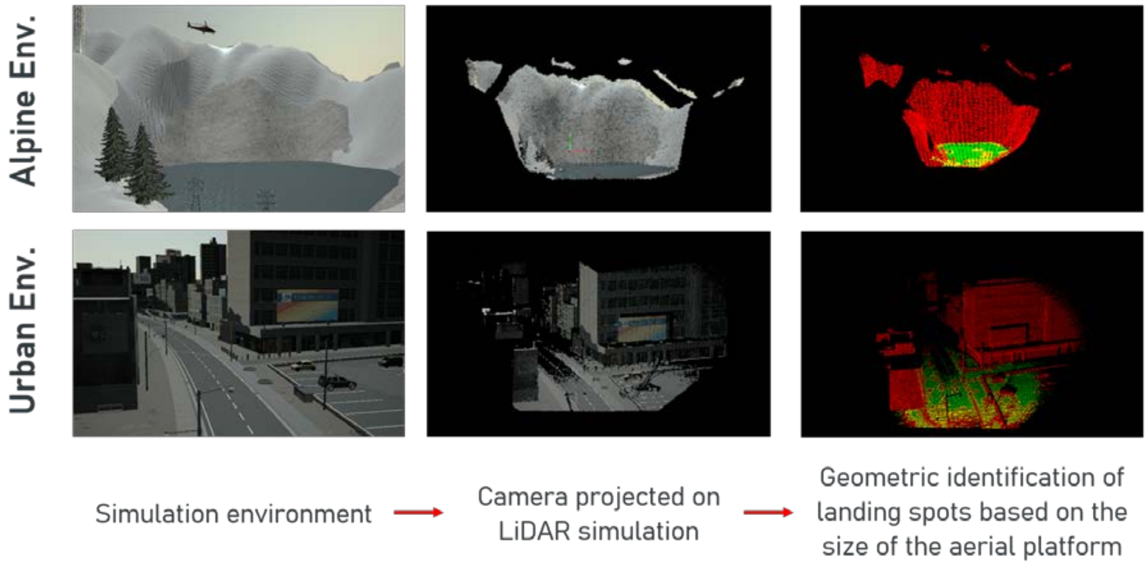

Figure 2: Geometry-based LiDAR processing and camera projection onto LiDAR point cloud - Images from the physics-based camera (left) are projected onto the data of the physics-based LiDAR (center) and an algorithm, combining point cloud local geometric features while being aware of the dimension of the helicopter, identifies feasible non-conventional landing spots (right).

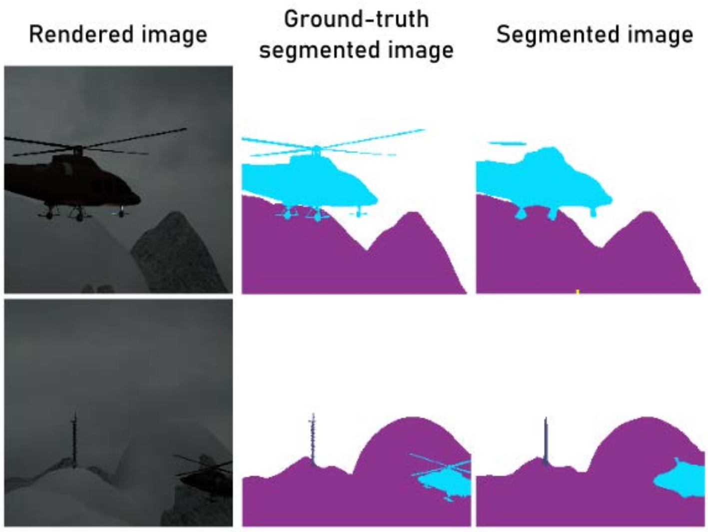

Figure 3: Image semantic segmentation architecture workflow - The rendered image (left) is the output of the simulator and it depends from the parameters of the simulated camera (e.g., resolution, field of view, color filter array (CFA)). Together with the rendered image, the simulator is capable of providing also a segmented image (center) that serves as a ground-truth of a dataset used for training, validation and test of our sensor-processing pipeline, including deep learning-based computer vision solutions. The figures on the right are examples of outputs from the computer vision pipeline. Note: the figures on the left and center are only examples and they are not part of the training used to train the architecture that we used to infer the figure on the right.

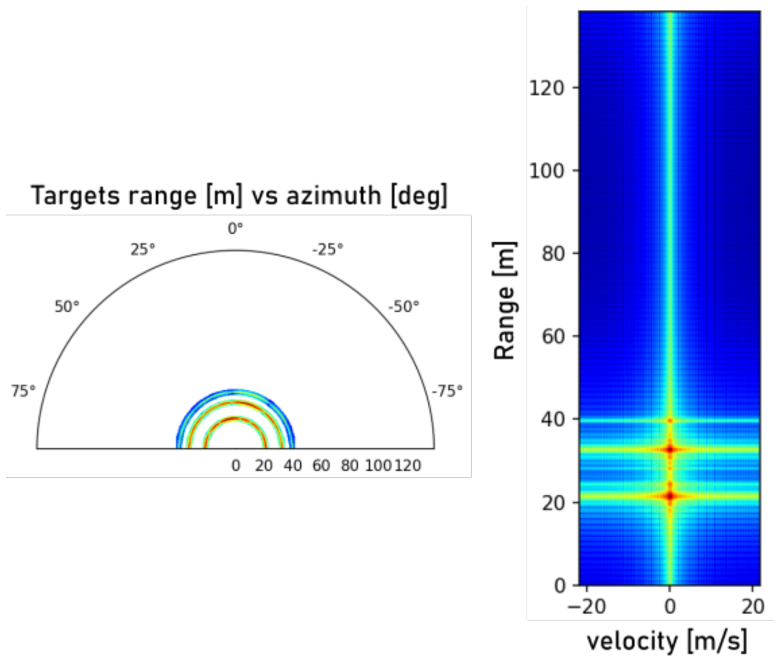

Figure 4: RADAR processing pipeline - Range-azimuth (left) and range-velocity plot of a RADAR synthetic acquisition in a test simulated scenario with three targets. Elevation is not shown, although available in our RADAR processing pipeline.

4.0 CONCLUSION AND FUTURE WORK

This abstract presents an approach to developing autonomous-flight functions based on both synthetic and real-world multimodal sensor data. The ideas discussed above are not novel in other sectors but, up to the authors' knowledge, have not been applied towards the enabling of autonomous flight of helicopters and other certifiable flying machines yet.

We will continue developing our autonomous-flight functions and we will keep improving the fidelity of the environments that we will use to test these functions. In particular, advanced multi-modal fusion techniques among the various sensors will be explored and implemented, such as fusing LiDAR data with RADAR output [17]. Regarding the image semantic segmentation, we will test different algorithms to understand which one fits better our needs (e.g., small objects, flying objects, highly diverse scenarios) [18]. One of the main challenges remains the capability of developing algorithms that are embeddable on a real helicopter or other flying machines with more stringent size, weight, power and cost constraints.

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