RESEARCH RESULTS AND PERSPECTIVES ON NON-COOPERATIVE SENSING FOR SAFE UAM OPERATIONS

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Abstract

In a world where UAVs are gaining an ever-increasing relevance in many aspects of the modern life, the safety of their operation is a key factor to be considered to achieve their full integration in the airspace. This is evermore relevant given the emerging ecosystems of Advanced and Urban Air Mobility which are pushing towards highly autonomous flight operations. The design of non-cooperative sensing strategies to detect and track small UAVs in low altitude scenarios is thus a topic of paramount relevance addressed by many entities at both industrial and academic level. This paper describes the recent results and the direction of the activities carried out in this frame at the University of Naples “Federico II”. In particular, the focus is set on architectures and algorithms for detection and tracking based on RADARs and optical sensors. Results achieved using a ground-based RADAR and an airborne camera are discussed, paving the way for novel sensing solutions which include the fusion of ground and air sensors. This latter aspect is among the near-term research perspectives whose general overview is introduced in the paper.

Keywords: Urban Air Mobility, Unmanned Aerial Vehicles, Non-cooperative Sensing, radar/visual tracking, sensor fusion

1. Introduction

In the context of highly autonomous vehicles, such as Unmanned Aerial ones (UAVs), a crucial aspect is the development of technologies enabling the capability to sense the surroundings of the platforms during operations with the aim of detecting any possible collision threat and performing avoidance maneuvers upon need. Such technologies, typically referred to as Detect and Avoid (DAA) or Sense and Avoid, play a crucial role in the integration of UAVs in both controlled and uncontrolled airspace where a reliable autonomous traffic awareness solution is required for safe operations of all platforms (either manned or unmanned), and have thus been one of the main focal points of the research community in the last 10 years [1]-[3]. During the initial phases of investigation major attention was draught to DAA concepts of operations for medium-to-large sized UAVs [4]-[5] whose high-altitude mission profiles, dimensions and dynamics are strongly different from those of the small UAVs class. Nevertheless, the recent skyrocketing trend in the market of the latter, fueled by the interest of worldwide industries, has brought an inversion in the direction of the research efforts which are now also probing novel DAA solutions for lower altitudes, i.e., below 150 m. In this framework, the rise of Advanced Air Mobility (AAM) and Urban Air Mobility (UAM) visions [6], foreseeing the use of UAVs and autonomous Vertical Take-Off and Landing (VTOL) aircraft for the transportation of people and goods in and around urban areas, acts as an amplifier for the development of surveillance solutions to localize the flying platforms both from the ground and from the air. In this specific case, an innovative solution is represented by the distributed sensing concept [7] which envisions the use of multiple sensors deployed in different locations and interacting to increase the surveillance volume.

For DAA and AAM/UAM surveillance solutions to be achieved, sensing strategies must be designed to reliably and accurately detect and track small targets flying close to the ground. Furthermore, to account for all types of platforms, either transponder-equipped, i.e., cooperative, or not, such solutions should exploit information retrieved by sensors which do not rely on any information broadcasting. This choice leads to the definition of non-cooperative DAA and surveillance strategies which encompass the use of both active and passive sensors. Research studies have spanned throughout all types of sensors, testing LiDAR-based DAA [8] as well as acoustic-based sensing solutions [9] as active and passive sources of information, respectively. Still, greater attention has been reserved to the testing of RADARs and visual cameras, identified as the most suitable choices for the application. Three-dimensional positioning information can be retrieved with the former up to hundreds of meters in distance and fairly independently from the external weather conditions. Research works such as [10]-[12] prove that using Frequency Modulated Continuous Wave (FMCW) RADARs can provide detection ranges as high as one kilometer, though measurements suffer from the presence of clutter when used in low altitude conditions. When visual cameras are used, higher accuracy in the bearing estimate field is achieved instead, though performance degrade with the adversity of the environmental conditions. In this context, the advancements in the machine vision sector and the advantageous dimensions and power budgets of the sensors have promoted a rise in the use of visual cameras for small UAVs detection as witnessed by numerous works which either deal with Neural Network-based detections, such as [13], or with morphological filters and frame differencing approaches [14]. As a result of the complementarity between the performance of RADARs and visual cameras, fusion of their heterogeneous information can be exploited to design a reliable non-cooperative sensing architecture achieving highly accurate relative positioning information built on range measurements from the RADAR (with the opportunity of also estimating range rate if Doppler RADARs are used) and bearing measurements from the camera. Some examples of fused solutions can be found in references [15]-[16] which exploit Kalman filters to track objects and design fusion at different levels, thus acting either during detection or directly during tracking.

The development of innovative non-cooperative sensing strategies for DAA and AAM/UAM surveillance is a core research activity carried out by the Aerospace Systems team at the Department of Industrial Engineering of the University of Naples “Federico II”. Following the thread of other research groups, solutions for UAVs of medium dimensions have been investigated at first, using either standalone airborne RADAR devices [17] or fused visual/RADAR approaches [5]. These solutions have been readapted to the case of lower altitudes and smaller UAVs in more recent works dealing with visual-based approaches [18] and their fusion with FMCW RADARs [19]. Most recently, efforts are being made in the direction of distributed sensing for AAM/UAM surveillance. In [20] the authors have detailed a fused solution for a network of ground-based RADARs to increase the area to be monitored and the temporal length of tracks of UAVs. All these works remark the relevance of experimentally testing the developed strategies to both build sensing architectures which are tailored for real world scenarios and foster innovations overcoming the existing challenges and bridging the gap with the requirements on accuracy, reliability and robustness. Therefore, datasets containing visual and RADAR measurements have been created and augmented yearly to support the development of sensing algorithms using visual cameras for air-to-air detection and tracking [18] or ground-based RADARs and visual cameras for ground-to-air detection [19]-[20]. In the latter case, a dataset of approximately 25 terabytes of RADAR and visual data capturing the flight of up to five small UAVs was built during joint experimental activities with the research team of the Aeronautic Systems Engineering Branch at the NASA Langley Research center during the summer of 2023 [21].

In this paper, the most recent experimental activities carried out by the authors are outlined providing details and first results on the application of RADAR and visual sensing strategies for small UAVs in low altitude conditions. The tests involve two small UAVs flying on collision courses collecting visual data with forward-looking cameras installed onboard. A multi-sensor, ground-fixed sensing node combining a visual camera and a FMCW RADAR is also used to collect data of the two UAVs during their flight. Specifically, ground-to-air RADAR tracking is performed using an Extended Kalman Filter (EKF) while air-to-air visual tracking, supported by a Convolutional Neural Network (CNN)-based visual detector, is performed on one platform (ownship) using two linear Kalman filters to estimate the horizontal and vertical relative position of the second platform (intruder) in terms of Line Of Sight (LOS) and Line Of Sight rate (LOSrate). Performance of the different tracking solutions is evaluated by exploiting a centimeter-level accurate benchmark evaluated with Carrier Phase Differential Global Navigation Satellite System (CDGNSS) data.

The remainder of the manuscript is structured as follows. Section 2 overviews the strategies used for the ground RADAR tracking and the airborne visual sensing tasks. Section 3 details the experimental activities performed and the results thereof while Section 4 and 5 provide conclusive remarks and perspectives on the research directions in the field of DAA and AAM/UAM surveillance.

2. Non-cooperative Sensing Algorithms

2.1 RADAR Sensing

The RADAR sensing strategy used on the data collected during tests is detailed in [19]. The strategy exploits an EKF with Nearly Constant Velocity (NCV) dynamics model whose state is expressed as $\mathbf{x}=[x,y,z,\dot{x},\dot{y},\dot{z}]$ where the first three components (x,y,z) are the components of the target relative position vector with respect to the North-East-Down (NED) reference frame centered at the RADAR location while the last three components $(\dot{x},\dot{y},\dot{z})$ represent their rates. The measurement vector used within the tracker contains measurements of range, R, azimuth, az, elevation, el, and range rate, Rrate, arranged as $\mathbf{z}=[R,az,el,Rrate]$. Such measurements are retrieved in the device reference frame and rotated in NED by exploiting the knowledge of the sensor-to-NED rotation matrix. Before being passed to the tracker and rotated, radar measurements undergo a filtering stage to reduce clutter and extract measurements of interest, e.g., all flying obstacles. Filtering is first performed setting a threshold on the range rate measurement, which needs to be large enough to avoid fixed obstacles (typically located in the proximity of the ground), and on the Radar Cross Section (RCS) signature of each detection. The latter threshold is set according to the typical RCS of small UAVs. The filtered measurements are also screened to identify clusters of detections which are logged at the same timestamp and belong to the same target. Such detections result from the RADAR scanning mechanism and can be identified using their difference in R, az and el which must be comparable to the radar range resolution, azimuth step and elevation step, respectively. These latter quantities represent the angular step between two consecutive RADAR beams.

A flowchart of the tracking algorithm is provided in Fig. 1. The algorithm is structured with three consecutive blocks which are used to pass from first track attempts, i.e., one-plot tracks, generated with all available measurements, to reliable tracks, i.e., firm tracks. One-plot tracks can become firm, after passing through the tentative track phase, if they meet association criteria based on the Mahalanobis distance. To avoid tracking errors divergence, tracks of all types are deleted if unsuccessful association, or lack of measurements, is verified for a time span which exceeds pre-defined thresholds varying depending on the type of track.

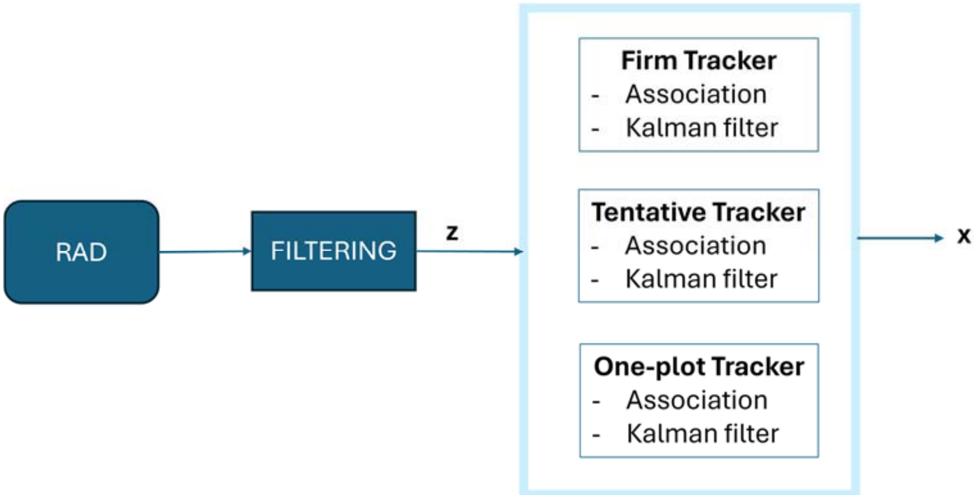

Figure 1 – Flowchart of the ground-based RADAR tracking procedure. “RAD” refers to the RADAR device, “FILTERING” refers to the procedure for clutter removal.

2.2 Visual Sensing

Details on the visual sensing strategy for the air-to-air detection and tracking task are thoroughly described in [18] and summarized in this sub-section. The tracker estimates the horizontal and vertical LOS components in the NED frame centered at the instantaneous location of the ownship which are expressed in terms of the state vectors of two independent NCV-based Kalman filters as $\mathbf{x}_{az}=[az,\dot{az}]$ and $\mathbf{x}_{el}=[el,\dot{el}]$, respectively. These vectors contain the azimuth, az, elevation, el, and their rates, $\dot{az}$ and $\dot{el}$, of any detected object. The measurement vectors are expressed as $\mathbf{z}_{az}=[az]$ and $\mathbf{z}_{el}=[el]$ where the az and el angles are estimated by exploiting the inverse mapping transformation from pixel coordinates to bearing measurements using the intrinsic camera parameters, known from calibration, as well as the attitude estimate. Pixel coordinates, i.e., (u,v), are the output of the YOLO v2 CNN object detector applied to the frames collected by the camera onboard the ownship. The output of such detection stage also reports the score, or confidence, associated to each detection thus making it possible to set a threshold (S_{th}) above which detections can be used for tracking. Given the geometry of tests, where the intruder platform flies above the ownship, only detections which are above the horizon line are used during tracking. Such line can be projected on the image plane exploiting the knowledge of the current altitude and attitude of the ownship as detailed in [18].

As in the RADAR case, the two visual trackers also exploit the principle of generating firm tracks from one-plot ones, as visible in Fig. 2. However, in this case some substantial differences can be found. Firstly, one-plot and tentative tracks are not predicted using the classical Kalman filtering theory. Instead, prediction of the LOS is performed by compensating for the attitude change between the current frame, *i*, and the next one, *i+1*. Such compensation is carried out by accounting for the attitude of the Body-Reference-Frame (BRF) in NED, thus representing the attitude of the whole drone in the world, and the attitude of the Camera-Reference-Frame (CRF) in BRF. Such attitudes can be parametrized with the NED-to-BRF (M_N^B) and the BRF-to-CRF (M_C^B) rotation matrices, respectively. The former can be evaluated using the 3-2-1 sequence of Euler angles rotation of heading (ψ), pitch (θ) and roll (φ) provided by the UAV navigation system. Likewise, the latter is evaluated using the mounting angles of the camera in the BRF, which can be estimated with extrinsic camera-inertial calibration procedures. Another difference with respect to the RADAR tracker lies in the association methods used at each block. At one-plot and tentative stages, association is deemed successful if the Euclidean distance between the predicted location of the target on the image plane and its current measurement is smaller than a threshold (d_{th}) which is used to avoid the generation of tracks of targets with fast angular dynamics with respect to the camera. Targets of this type, such as birds, do not represent a collision threat and are thus discarded from the firm tracking process.

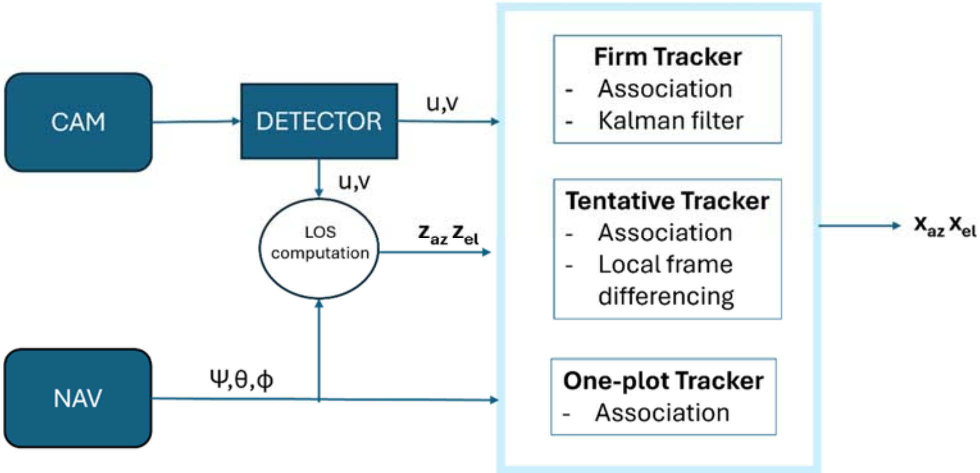

Figure 2 – Flowchart of the visual air-to-air tracking procedure. “NAV” refers to the UAV onboard navigation system, “CAM” refers to the UAV onboard camera.

3. Non-cooperative Sensing Results

3.1 Experimental Tests

The experimental tests involved the use of two UAVs piloted to perform near collision encounters. The platforms used during tests, shown in Fig. 3, are two customized DJI M100 platforms (highlighted in blue and red in the figure) and a DJI M200 platform. For the scope of this paper, the flight of the two M100 is used to discuss preliminary results of air-to-air visual tracking and ground-to-air RADAR tracking. For this application, Athena (blue-highlighted UAV in Fig. 3) is chosen as the ownship while Eagle (red-highlighted UAV in Fig. 3) is chosen as the intruder. Therefore, visual data collected with the camera installed onboard Athena is used to detect and track Eagle during its flight. The payload configuration on both platforms is very similar. Athena is equipped with a FLIR Blackfly visual camera (BFLY-U3-50H5C-C) with 5.0 megapixels acquiring RGB frames with a frequency of approximately 7 Hz. A similar camera is also installed on Eagle, though its data are not used in the context of this paper. To perform CDGNSS-based computation of the relative position between the two UAVs, auxiliary GNSS receivers and antennas (uBlox LEA-M8T) are also installed on both platforms. The acquisition of the payload data is carried out using the Robot Operating System (ROS) framework installed on Intel NUC onboard computers with Ubuntu operating system. The constitutive parts of the payload onboard Athena are shown in Fig. 4.

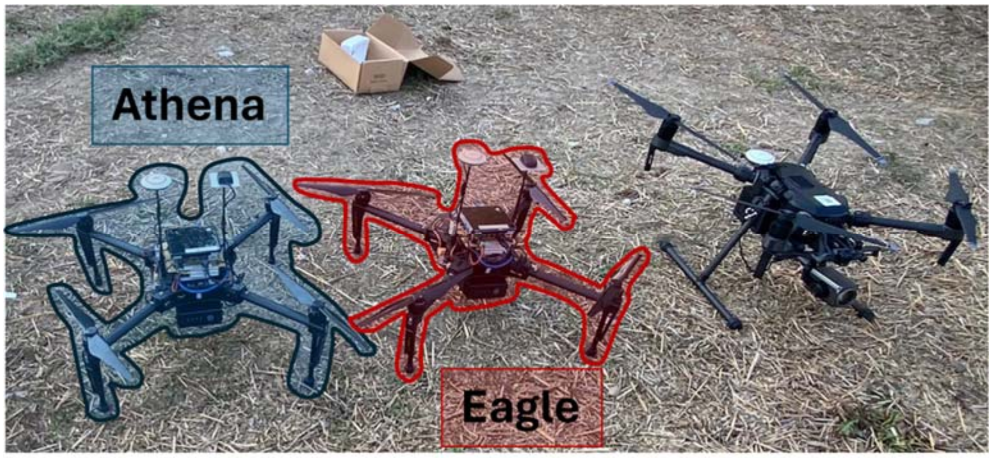

Figure 3 – Drones used during experimental tests. Drones used for the results discussed in this paper are highlighted in blue (ownship – Athena) and red (intruder – Eagle).

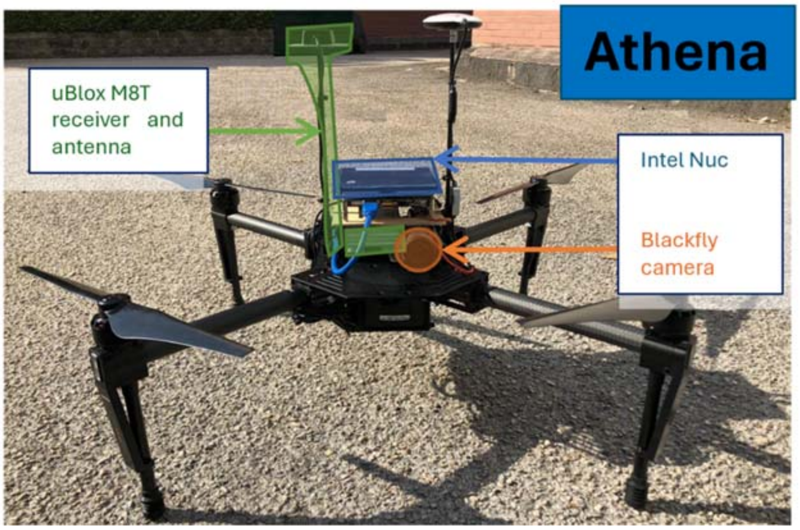

Figure 4 – Payload onboard Athena (ownship).

The ground sensing segment used during experiments is shown in Fig. 5. It comprises an Echoflight MESA radar, manufactured by Echodyne, and a 3.1 megapixels FLIR Blackfly camera acquiring RGB frames at 10 Hz frequency. The radar is used in Search-While-Track mode, collecting measurements also at a frequency of approximately 10 Hz while scanning a Field Of View (FOV) of about 90° and 45° in the horizontal and vertical directions, respectively. A uBlox F9P GNSS receiver and patch antenna is also used on the ground for CDGNSS computation, thus retrieving a benchmark for the relative positions of both Athena and Eagle with respect to the ground setup.

The results of the CDGNSS processing with respect to the ground sensors is shown on a satellite map, thus in terms of latitude and longitude, in Fig. 6.

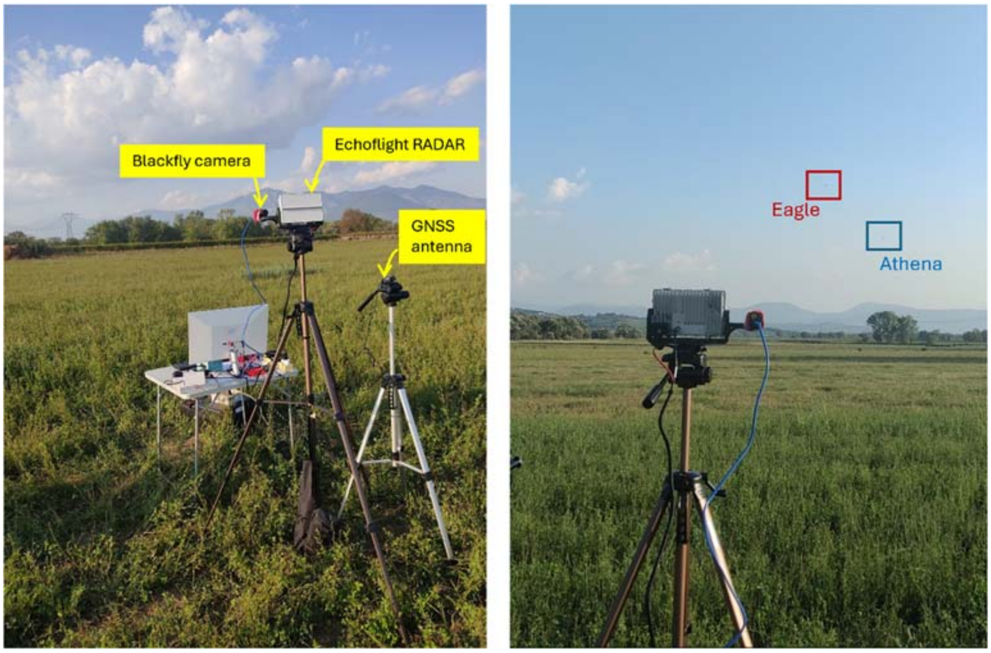

Figure 5 – Ground-based sensing setup. A snapshot during Athena and Eagle flight is shown on the right.

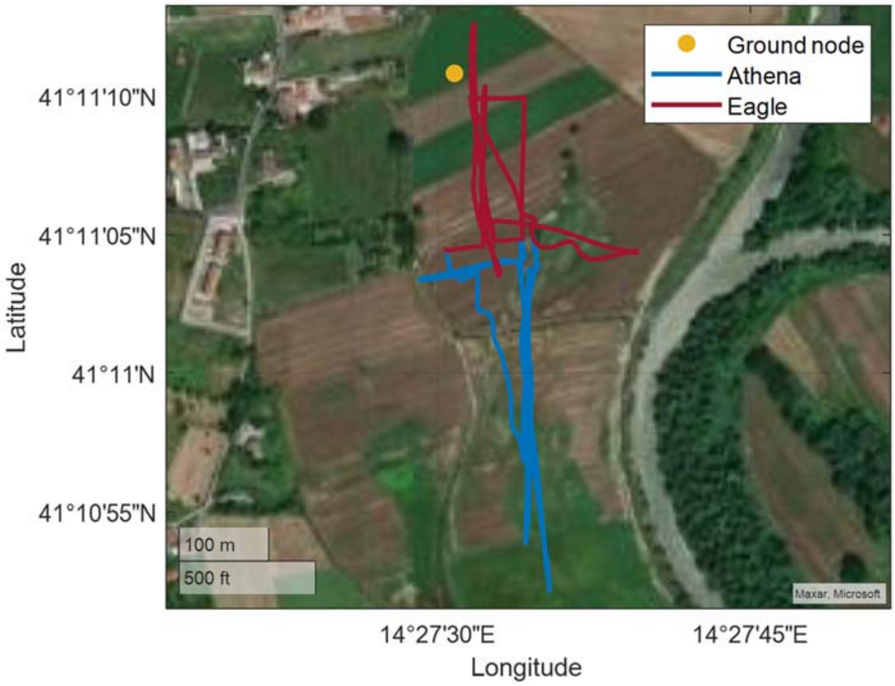

Figure 6 – Trajectory of Athena (blue) and Eagle (red) during flight as estimated with CDGNSS benchmark with respect to the ground sensing setup (location shown with a yellow dot).

3.2 Ground-to-air RADAR Sensing Results

The results of the ground-to-air RADAR firm tracking procedure are shown in Fig. 7 and Fig. 8 where the estimated relative position of the two UAVs and their reference Ground Truth ("GT") are reported in cartesian and spherical coordinates, respectively. In Fig. 7, the reported estimates are limited to the tracks of the two UAVs only which are extracted from all generated firm tracks by thresholding their errors with respect to the GT. Fig. 8 shows all firm tracks generated by the RADAR tracking process instead, highlighting with different colors and line widths the tracks of the UAVs. The generation of other tracks, reported with grey lines in the figure, can be imputed to unfiltered clutter measurements.

The RADAR is able to follow the trajectories of the two UAVs quite continuously with interruptions which occur when the UAVs exit the FOV of the device. This is often the case of Eagle which flies more northerly with respect to Athena, thus surpassing the vertical limit of the FOV of the RADAR.

The firm tracking performance can be evaluated in terms of the Root Mean Square (RMS) error with respect to the reference. These show the expected fine accuracy in the range estimate, which is settled on 3 meters for both UAVs, and the coarser accuracy in the angular estimate, around 1° and 2° for the azimuth and the elevation, respectively.

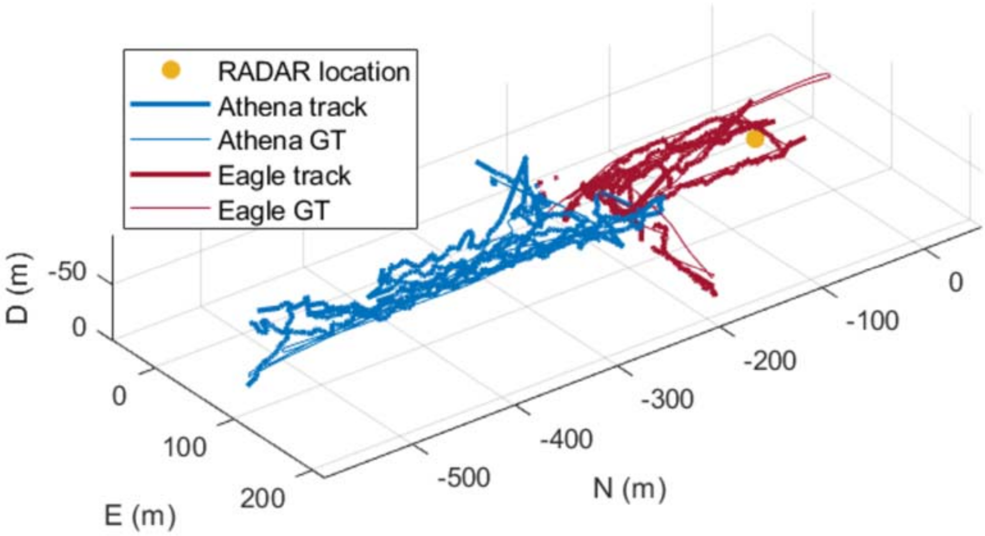

Figure 7 – Results of ground-to-air RADAR tracking along with CDGNSS Ground Truth. Location of RADAR marked with the yellow dot.

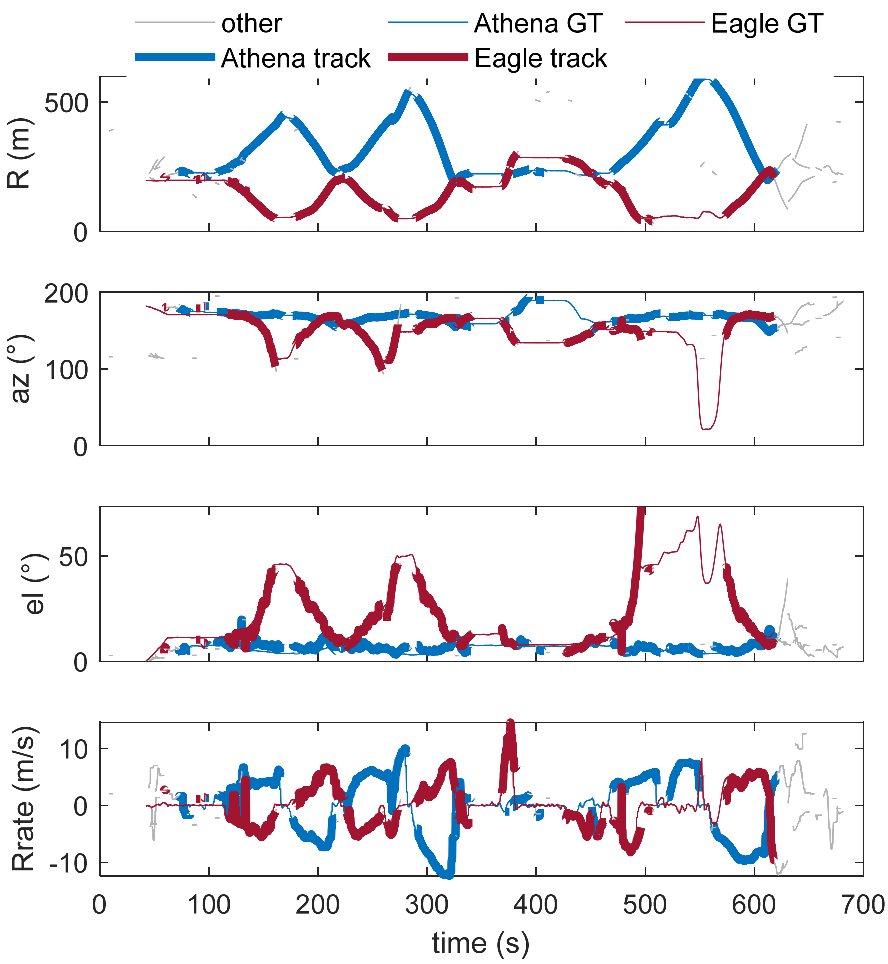

Figure 8 – Results of RADAR tracking in spherical coordinates with Rrate.

3.3 Air-to-air Visual Sensing Results

During the air-to-air tracking process, the CNN detector is applied on the frames collected by the camera onboard Athena and its detections are used if their score is greater than S_{th}=0.3. The association of one-plot and tentative tracks is evaluated using a threshold on the pixel distance of d_{th}=10 pixels.

The plots in Fig. 9 show the results achieved during firm tracking in terms of the estimated azimuth and elevation of Eagle, along with its GT, and other tracks (depicted with grey lines). As previously done for the RADAR, tracks of the UAV are extracted by thresholding their errors with respect to the CDGNSS reference. In this case, other tracks are generated from objects above the horizon line whose appearance is similar to Eagle's, thus being detected by the CNN with a confidence score greater than S_{th}. An example of such objects is reported in Fig. 10, where the firm track of Eagle (flying at about 200 meters form Athena) is depicted with a red circle while an additional firm track generated by a component of the power line on the left part of the image is also illustrated (black circle). The trajectory of Eagle with respect to Athena is followed by the tracker up to a maximum distance, as inferred by the CDGNSS GT, of about 420 meters when the projection of Eagle on the image plane only occupies few pixels, as shown in Fig. 11 left where the projection of the firm track of Eagle in pixel coordinates is reported as a red circle. A frame showing Eagle's track at about 40 meters from Athena is also shown in Fig. 11 right to provide a comparison in the dimensions of the target when approaching the ownship. Performance-wise, the RMS values achieved are settled around the degree level and below the degree level for azimuth and elevation, respectively. This discrepancy in the results can be imputed to residual errors in the estimation of the attitude of the CRF with respect to the BRF.

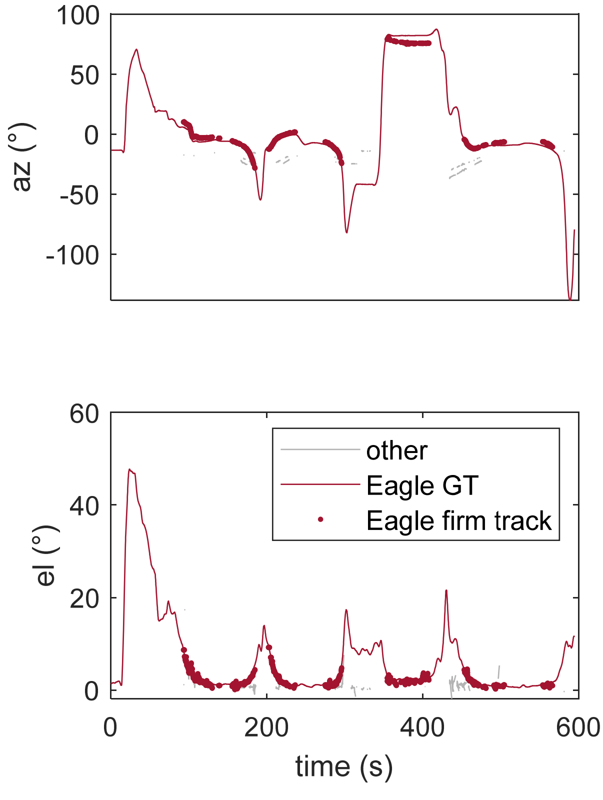

Figure 9 – Results of air-to-air visual firm tracking using Athena's onboard camera.

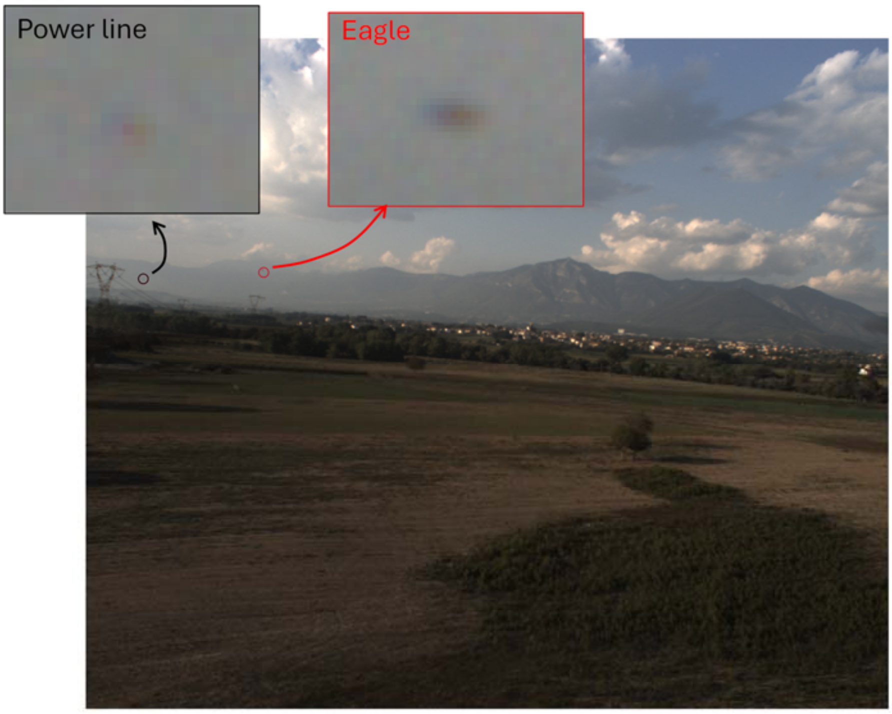

Figure 10 – Frame collected by the camera onboard Athena at t=177 s. Firm tracks at this time are reprojected on the image plane and depicted as circles.

Figure 11 - Frame collected by the camera onboard Athena at t=200 s (left) and t=550 s (right) showing projection of Eagle's firm tracks as red circles.

4. Research Directions and Perspectives

The development of DAA and AAM/UAM surveillance strategies represents an open area of investigation. The sensing strategies need to account for the challenges of detecting small objects flying in low altitude conditions with non-cooperative sensors.

The latest works carried out by the authors have highlighted that the sensing architecture can benefit from the use of multiple, heterogeneous sensors to improve robustness and performance. The fusion of RADARs and cameras can provide the needed high accuracy in the localization of targets while strengthening the whole system towards adverse weather and low illumination conditions, to which cameras are highly vulnerable, as well as interference phenomena, which may affect RADARs. Such a solution is undoubtedly easier to be achieved for ground-to-air surveillance infrastructures, which have lower requirements on power, size and weights of the sensors. Instead, requirements become more stringent for airborne platforms where installation of visual cameras is far more feasible. This results in the lack of a reliable distance information from possible collision threats for all flying platforms, causing the estimation of the state of targets to be incomplete. This issue can be solved by designing innovative interaction strategies between ground and air sensors which would leverage on the availability of accurate distance information, from the ground RADAR, to be broadcasted to all operating UAVs as part of a traffic awareness service. This strategy would thus enhance air-to-air DAA without major variations in terms of onboard payloads.

More in general, potential and challenges of ground/air interaction are emphasized within the emerging paradigm of distributed sensing. This framework provides several open points which can be addressed in the near term. Detection and tracking strategies at sensor level, as well as data fusion strategies, have to be adaptive with respect to the variable detectability of air objects in different environmental conditions, while ensuring minimum surveillance performance levels. This implies that the overall sensing system may provide outputs at different levels, depending on the amount of information and the capability to fuse the detections generated at sensor level. Data fusion approaches have to account for several aspects. Effective space registration of sensors' measurements requires proper knowledge of translation and rotation among sensor reference frames, which is obtained by ad hoc calibration strategies for ground-based sensors, and is time-varying for airborne nodes whose relative positioning and alignment is estimated by the onboard navigation systems. Time-registration of sensing information is also needed, so that synchronization plays a key role and the uncompensated latencies should be kept as small as possible. The design of data fusion strategies offers different possibilities in terms of location of processing centers, with different implication on the local communication network needed to support distributed surveillance. Furthermore, air/ground data fusion needs to consider cyber-security challenges in order to be resilient and robust.

Going beyond sensing algorithms, proper design and optimization of sensor networks represent promising paths for investigation. It is clear that simple techniques are not scalable to complex environments, thus paving the way for computationally efficient approaches to explore the design space. In the open framework of AAM and UAM, surveillance requirements and performance are not independent from airspace structure and management considerations. A bi-directional link exists between them, which can be investigated to find a reasonable trade-off between sensing complexity and costs, and required surveillance performance, under the main constraint of the required safety levels. Another interesting research path leads to surveillance-aware airspace rules, which avoid by construction the generation of relative geometries which challenge non-cooperative sensing capabilities. Finally, optimization of sensing resources can also be pursued by adaptive sensing approaches, which take traffic information and flight rules into account at surveillance level. For example, the idea is to exploit a priori known velocity limits to optimize the conflict detection trade-offs, or to adapt the detection algorithm parameters towards the required time to closest point of approach, thus automatically tuning the perception algorithms for near frontal or lateral encounters.

5. Conclusion

This paper provides an overview of the activities carried out at the University of Naples "Federico II" focused on the design and testing of non-cooperative sensing strategies for low altitude scenarios and small UAVs. The lates field tests performed in this direction are presented and some preliminary results on the use of ground-based RADAR and airborne visual tracking strategies are discussed. The tests performed involve the use of two small UAVs flying on collision courses which are captured by a ground sensing setup comprising a FMCW RADAR and a visual camera. The performance of the RADAR tracking approach proves the expected high accuracy in the distance estimate while the coarse angular accuracy can be improved exploiting fusion of the co-located camera. The results of the air-to-air visual tracking solution underline that the presence of a structured environment, with multiple static objects rising above the horizon line on the image plane, is a challenge to be coped with by applying stricter thresholding approaches in the generation of firm tracks. Further works will foresee the application of RADAR/visual fusion for the ground sensors and the development of a ground/air interaction strategy to enhance airborne DAA performance.

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7. Copyright Statement

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