SAND2022-9903C

MARCUS: A Framework for Heterogeneous Cooperative Autonomous Multi-robot System for Counter Uncrewed Aerial Vehicles

Antonella Barisic[1], Marlan Ball[2], Noah Jackson[2], Riley McCarthy[2], Nasib Naimi[3], Luca Strässle[3], Jonathan Becker[3], Maurice Brunner[3], Julius Fricke[3], Lovro Markovic[1], Isaac Seslar[4], David Novick[4], Jonathan Salton[4], Markus Möpflinger[5], Stjepan Bogdan[1], and Rafael Fierro[2]

***Abstract*— In this paper, we present a novel heterogeneous multi-robot system for cooperative autonomous counter-UAV missions. As UAV technology rapidly evolves, there is an immediate need for security solutions. We propose a solution that utilises 1) different complementary robotic platforms to achieve long-term cooperative operation, and 2) multi-modal perception for more robust and accurate sensing of the protected airspace. The developed system consists of a mobile ground vehicle with LiDAR sensor, a UAV with gimbaled stereo camera for air-to-air inspection, and a UAV with catching mechanism equipped with radars and camera. We report our hardware and software design, along with the results from extensive field testing. We demonstrate the successful integration of all subsystems and their efficiency in accomplishing the task at hand. The video results are available at:**

Fig. 1: MARCUS: Mobile Adaptive/Reactive C-UAS.

I. Introduction

The capabilities, speed, size, and widespread use of small uncrewed aerial vehicles (UAVs) [1] provide unlimited opportunities for their beneficial use, but also present a security concern that must be addressed. An intruder in protected airspace, i.e., any type of UAV that is not allowed to be in the airspace, must be countered in a safe and non-invasive manner to protect the area of interest. Typical use cases for the deployment of counter-UAS (C-UAS) systems include public gatherings, airports, hospitals, power plants, prisons, etc.

Potential intruders have a small cross-section and are difficult to detect reliably with purely ground-based systems (e.g., radar or electro-optical). Ground-based sensors are static and suffer from interference with the earth, vegetation, and other structures that obscure objects at low altitudes. Adding sensors to mobile UAV platforms improves detection accuracy and reliability by bringing on-board sensors closer to the target while reducing the signal-to-noise ratio. This is the idea behind the international collaborative project *Mobile Adaptive/Reactive Counter UAS System* (MARCUS), which combines complementary robotic platforms on the ground and in the air to form a cooperative autonomous multi-robot system. By working together and sharing information to successfully accomplish a specific task, multi-robot systems demonstrate better performance and are more robust, reliable, and go beyond the efforts of individual robots. Therefore, the proposed MARCUS framework provides an innovative solution to this global problem and includes three main elements: (i) detection, (ii) tracking, and (iii) interception and neutralization of the intruder with none or little collateral damage. In addition to using multiple different robotic platforms to complement their advantages and create a long-term energy-efficient system, we also develop a multi-modal perception to detect and localise potential intruders. The multi-modal sensing shows superior performance compared to uni-modal by being more abundant in information, more robust to changes in dynamic and unstructured environments, and is ultimately more accurate and reliable.

A. Related Work

Counter Uncrewed Aerial Systems is an active area of research. A report by the Center for The Study of Drones

This work was supported by NATO Science for Peace and Security Programme.

[1]Antonella Barisic, Lovro Markovic and Stjepan Bogdan are with the Laboratory for Robotics and Intelligent Control Systems (LARICS), Faculty of Electrical Engineering and Computing, University of Zagreb, 10000 Zagreb, Croatia {antonella.barisic, lovro.markovic, stjepan.bogdan}@fer.hr

[2]Marlan Ball, Riley McCarthy, and Rafael Fierro are with the Electrical and Computer Engineering Department, University of New Mexico, Albuquerque, NM 45435, USA mball15@unm.edu, rmccar@unm.edu, rfierro@unm.edu

[3] Nasib Naimi, Luca Strässle, Jonathan Becker, Maurice Brunner and Julius Fricke are with Autonomous Systems Lab (ASL), ETH Zurich, 8001 Zurich, Switzerland nasib.naimi@ethz-asl.ch

[4]Isaac Seslar, David Novick, and Jonathan Salton are with Sandia National Laboratories, Albuquerque, New Mexico, 87185, USA, a multi-mission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC., a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525. Sand Number: SAND2022-XXXX X

[5]Markus Höpflinger is with the Federal Department of Defence, Civil Protection and Sport, armasuisse S+T.

identified 537 counter-drone products on the market or in development as of 2019 [2] (c.f., 235 in Feb 2018). Although aerial vehicles have shown great potential in solving various critical and difficult tasks [3], the growing autonomy of UAS posed a threat to the security of individuals and organizations alike such as airport control tower, or perform unwanted surveillance in a protected space [4], [5], [6].

The multi-agent pursuit-evasion problem has been studied throughout the years. In traditional pursuit-evasion games, a pursuer tries to capture evaders, while an evader tries to evade capture from the pursuers. The authors in [7] used the area minimization strategy as a mean to intercept rogue robots. The strategy seeks the best coordination to minimize Voronoi cells of evaders. Similarly, the authors in [8] solves cooperative pursuit problem by partitioning the operational space into Voronoi regions and developing a control strategy that allows each pursuer to occupy the regions, thus increasing the probability of capturing the evaders.

One variation of the pursuer evasion problem is in the form of perimeter defense game as described in [9]. The authors developed an algorithm to intercept a group of evaders trying to reach a target area. Another variation of the the pursuer evasion problem is described in [10], where the policies are developed for two pursuers to intercept any incoming threat. The authors described several intercept strategies for catching an evader. Another variation is described by [11], where the designed policy is to herd a group of swarm evaders to a safe area. The authors developed a stringent algorithm to herd the attackers to a safe area away from a target space.

In our previous work [12], we proposed an air-to-air approach, entitled *Aerial Suppression of Airborne Platforms* (ASAP), which used defensive UAS in coordination with ground-based systems. The objective of ASAP was to detect, track, and, if needed, neutralize small threat UAS using multiple aerial pursuers. By moving airborne sensors and precision defense systems away from ground interference and near to potential threat vehicles, this approach exploited geometric advantages, such as multiple perspectives, significantly increased angular cross section, and the ability to use short-range precision maneuvers for neutralization. We focused on the tracking component of ASAP [13], i.e., the interception of a small threat whose intentions may or may not be adversarial, and leveraged the results presented in [14], which provided a globally optimal solution, using multiple convex optimization problems, to the path planning problem for a single pursuer in pursuit of a non-adversarial stochastic target. Global position information was provided by a VICON motion capture system. A similar indoor approach is described in [15] where a *hunter* UAV autonomously detects and hunts a small UAV in GPS-denied environment. The platform detects another drone using a pre-trained machine learning model.

Vision-based UAV detection and classification has been addressed in [16], [17], [18], [19]. A novel approach to generate a synthetic aerial dataset for UAV detection, considering the imaging conditions specific for air-to-air, namely long-range detection and detection under changing illumination, is developed in [20]. RF is another method of drone detection that have received a lot of attention, see for instance [21].

Neutralization is possibly the most critical and difficult component of a C-UAV system. We only consider air-to-air neutralization methods in this review [22].

B. Contributions and paper organization

The main focus of this paper is to demonstrate how different robotic platforms and different sensor modalities provide a reliable and robust solution to ensure the safety of the airspace. The core contributions are:

- A novel framework for autonomous cooperative C-UAS operations using a heterogeneous multi-robot system consisting of a mobile ground vehicle for long-term patrolling, a UAV for close-range air-to-air inspections, and a UAV with the capability to safely retrieve the intruder.
- A multi-modal perception framework for multirotor UAV detection and localization using four different sensor modalities: Light Detection and Ranging (LiDAR), stereo camera, radar, and monocamera.
- A design, development and validation through field testing of three different robotic platforms for C-UAS missions.

The remainder of the paper is organized as follows: Section II formulates the problem of the pursuit-evasion game, while Section III describes the technical details of the design and construction of the robotic platforms applied in the proposed framework. In Section IV, multi-modal perception is described in detail, along with a brief description of the high-level control algorithms. Section V presents the findings and results of the field tests and the fully integrated end-to-end mission.

II. Preliminaries and problem formulation

The problem addressed in this paper is a complex variant of the pursuit-evasion game (PEG). Our system consists of five types of agents: target, intruder, patroller, pursuer, and interceptor. The target in this PEG is the center of the protected area, making it a target-guarding problem. The intruder is an unknown aerial vehicle that enters protected airspace. The intruder is non-cooperative but its intent is unknown, as it could be a stray vehicle or a threat. The patroller is a ground vehicle equipped with a sensing system for long-term patrolling over the protected area. The second agent capable of sensing the intruder is the pursuer, a UAV for air-to-air inspection and verification of a possible intruder. And finally, the interceptor is a UAV for fast and safe interception of the intruder. The complexity of the presented problem arises not only from the number of different agents and their roles, but also from the need for cooperation between the agents.

Our scenario takes place in a predefined region of interest. The number of each agent type can be scaled to achieve desired coverage. Each agent type has a unique role, meaning

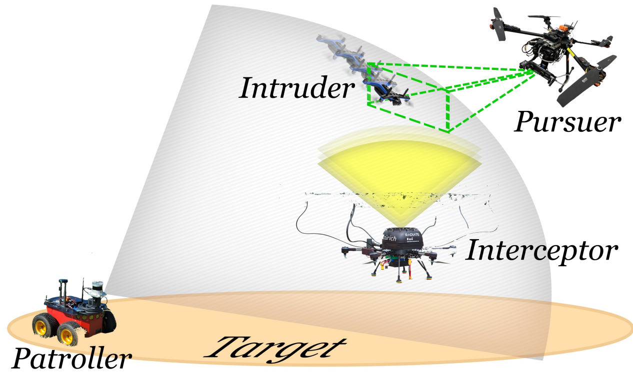

Fig. 2: Overall MARCUS system.

others may be dependent on its actions. They compliment each other to provide best coverage with taking into account operating time and efficiency. The developed framework can handle an unlimited number of intruders over time, but assumes one intruder at a time.

III. Architecture for C-UAS

In this paper, a heterogeneous system of cooperative autonomous robots is presented. Each robot is equipped with different set of sensors to take full advantage of specific platform. Details of the hardware components are presented below.

TABLE I: Operational time of each agent

Agent	Patroller UGV	Pursuer UAV	Interceptor UAV
Operational time	10 hours	20 mins	10 mins

A. Mobile Ground Vehicle

In the framework developed for the MARCUS project, the patroller agent is implemented using a mobile uncrewed ground vehicle (UGV). The goal of the patroller is to operate over long periods of time and perform initial detection of potential intruders. We selected the Pioneer 3-AT, a mobile platform with two motors on each side connected with timing belts, allowing skid-steer, all-terrain operation. The Pioneer is controlled by Pixhawk running ArduRover autopilot software, and Jetson Xavier NX as the onboard computer. The patroller is equipped with an Ouster OS0-128 LiDAR mounted on a Directed Perception Pan-Tilt Unit (PTU). The Ouster OS0-128 has 128 beams with a 90-degree vertical field of view (FOV) and 2048 readings at 10Hz in each 360-degree scan. The UGV is powered by 5 separate batteries that provide long-term operation in the range of 10 hours.

B. UAV for Inspection and Verification

The pursuer UAV platform was designed and built specifically for the MARCUS project. The pursuer is a mid-sized quadcopter with full onboard computation. The frame is the Iron Man 650 Folding Frame from Tarot. It is a 650mm diameter quadcopter frame with four T-Motor Antigravity MN5008 400KV motors spinning T-Motor MS1704 carbon fiber propellers and are driven by T-Motor Air 40A ESCs. The UAV is controlled by a Pixhawk Cube Orange with a full sensor suite running Arducopter, which receives commands from an NVIDIA Jetson Xavier NX. The full autonomy stack runs on the Jetson. The Jetson receives stereo image data from a Stereolabs Zed Mini camera mounted on a custom two-axis gimbal being stabilized by two Savox SAVSW2290SG-BE servos which are controlled by the Pixhawk. The whole system is powered by a 10000mah 6s (6 cells) battery that can keep the drone in the air for about 25 minutes. This drone is capable of speeds in excess of 95 kilometers per hour.

C. UAV for Interception

For interception of an intruder a custom UAV platform was built. It is a hexacopter equipped with six Mad Components 5008 400KV motors and six T-Motor F45A-32bit 3-6S ESCs. The frame is a custom design and consists of two carbon plates and six carbon tubes. A catching mechanism is mounted on top of the UAV. It consists of a structural net to transfer the energy of the impact to its six arms, which are made from carbon fibre and are designed to absorb the impact of this task in an optimal way. On top of the structural net there is a second, thinner net which entangles the propellers of the intruder UAV during a catch. Pointclouds generated by two Texas Instruments AWR1843AOP millimeter-wave radars in different configurations and images from a Flir Chameleon3 color camera are processed by the onboard computer, an NVIDIA Jetson Xavier NX. The onboard computer also runs the full software pipeline enabling autonomy. It sends body rate and thrust commands to a Pixhawk 4 flight controller running PX4 firmware. The radars and the camera are protected by a 3D printed dome covered with plexiglass. Powered by two 5000mAh 6S (6 cells) batteries, the whole system reaches a flight time of approximately 10 minutes.

D. Ground station

A cooperative mission of our multi-robot system is monitored via a graphical user interface (GUI), as shown in Fig. 3. The presented GUI is tailored for C-UAS operation, but is generally used for various operations of multiple UAVs, as explained in [3]. A human operator can track the state of each robot (e.g., idle, tracking, or approach) and observe their GPS locations on a preloaded offline map. Since all algorithms are computed online, the robots report only the most relevant information to the ground station. The final output of the sensing algorithms is transmitted to the ground station and displayed on the map as the GPS location of the detected intruder.

The developed system can be end-to-end autonomous or can adopt human-in-the-loop (HITL) approach. In our experiments, and most likely in industrial applications, we use the HITL approach. An important aspect in this process is the cropped RGB image of the detected intruder, which is transmitted from the pursuer UAV. The visual detection of the intruder provides rich data to the human operator, based

Fig. 3: GUI for C-UAS operation

on which various decision can be made. Starting from the possibility of a false detection (e.g., a bird) to the need for immediate mitigation. The human operator acts as an additional layer of safety in the system, and his confirmation of the detected intruder is requested upon successful detection, either coming from ground vehicle or pursuer UAV. Our goal is to achieve the highest level of safety while allowing the robots the highest level of autonomy.

IV. Sensing and Mitigation

In this section, we describe three principal components of counter-UAS system: detection, tracking, and mitigation. Detection refers to processing sensor data and analysing it to extract valuable information, such as whether an intruder is in a protected area and where it is. Each of our robots had this component and is based on different sensor data. In this way, we leverage advantages of different sensor modalities to increase the probability of detecting possible intruders. The next step is to track the intruder over a longer period of time to get a better insight into his intentions and the necessary information to plan future actions. Once we have all this, we proceed to mitigation by safely removing the risk while ensuring no or minimal damage.

A. *LiDAR-based detection*

Initial detection of intruders is accomplished by analysing point clouds from a LiDAR sensor mounted on a pan-tilt unit (PTU). The patroller runs a waypoint mission on the outer boundaries of the protected area, as shown in Fig. 7. The patroller stops at each waypoint to scan and search for possible intruders. The Ouster OS0-128 has a vertical angular resolution of 0.7°, resulting in a vertical distance between two beams of 61cm at a distance of 50m, which is the maximum range reported by the manufacturer. This gap provides enough space for small UAVs to avoid detection. For this reason, we constantly tilt the LiDAR sensor during scanning phase.

We narrow the azimuth window of the LiDAR to 120°to reduce the amount of data to be processed. We also increase the signal strength to 3x to improve the detection probability. The other parameters of the sensor are set to the default values. We apply the necessary transformations based on the data from GPS and the data from PTU encoders to transform

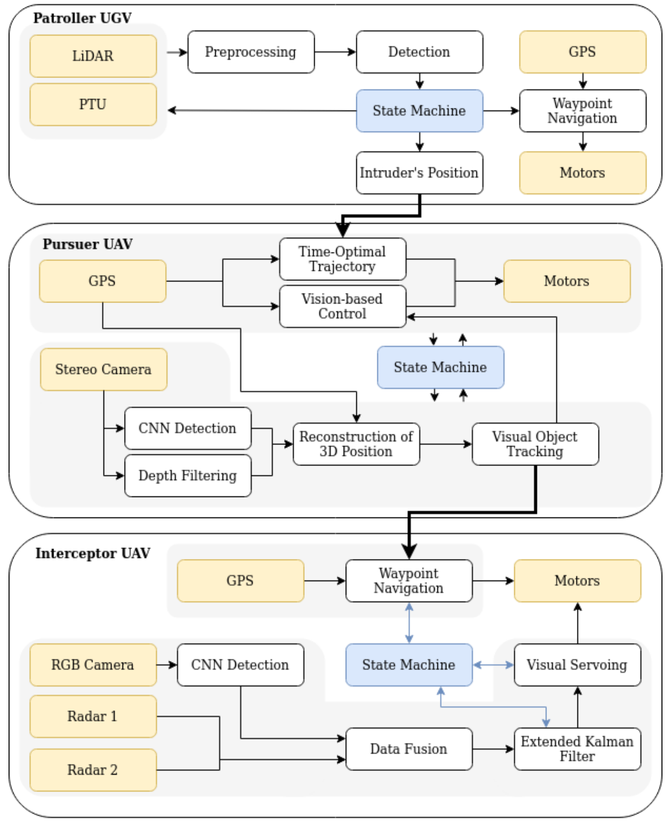

Fig. 4: Overview of the software architecture for a cooperative robotic system with multi-modal perception. The heterogeneous system is comprised of an autonomous ground vehicle (patroller) and two task-different UAVs (pursuer and interceptor). The yellow color highlights the sensors and the blue color highlights the decision part of the system. Only the most important components are shown.

the point cloud. The point cloud is preprocessed to filter out data that lies outside our protected airspace. On the filtered point cloud we detect intruders by applying the Euclidean clustering algorithm. The output clusters are considered as candidates for further inspection by the pursuer UAV. The GPS location of the intruder is reported to the GUI and to the pursuer UAV.

B. *Vision-based detection and tracking*

Upon successful detection from LiDAR sensor, the pursuer UAV starts its mission and begins the search accomplished by time-optimal trajectory. The trajectory is in the form of spiral, oriented towards reported location and narrowing inward. The position reported by LiDAR is only used to cue pursuer UAV to a approximate location, as UAV has its own detection system for a more detailed investigation. Searching over a larger area and getting closer to the reported location increases likelihood of detecting the intruder even if it changes position, which is very likely. During the search, the convolutional neural network (CNN) processes the right image of the stereo pair. In this work, we deploy YOLOv4 Tiny trained on the synthetic dataset described in [7] and fine-tuned on a smaller subset of real images.

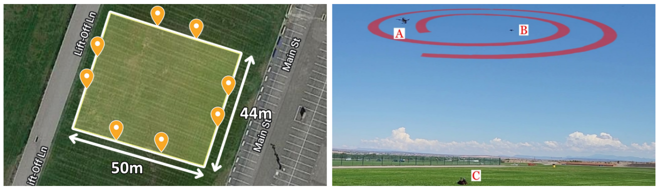

Fig. 5: Left: waypoint mission of the patroller UGV equipped with LiDAR sensor. Right: the pursuer UAV (A) in spiral search for the intruder (B) after receiving initial detection from the patroller UGV (C).

If an intruder is detected, we filter the depth data based on the techniques described in [2] to remove noise and ensure reliable measurements for control. As shown in Fig. 4, the output of CNN detection and depth filtering are then used to reconstruct the 3D position of the intruder using the pinhole camera model. The linear Kalman filter with the constant velocity model is then used for visual object tracking (VOT). The output of VOT is forwarded to the position-based visual servoing to navigate the pursuer towards the intruder. Our goal is to keep the intruder at a safe distance and in the center of the image, slightly above the horizon. Based on the sensor inputs and the data received from the other robots, the state of pursuer UAV is controlled by a finite state machine. The pursuer UAV sends the GPS location of the intruder to the interceptor UAV in response to the request to intercept it, and waits for the interceptor to respond that it is approaching for safe mitigation.

C. Mitigation

The interceptor autonomously takes off and moves below the received GPS position, where the images of the upwards-directed camera are processed by a CNN based on YoloV4 Tiny architecture, similar to the one mentioned in Section IV-B. This model was trained to detect drones in an overexposed sky from below the target drone looking upwards. Furthermore, the two radars search for any objects in their field of view. Upon detection of the intruder by both image and radars, an Extended Kalman filter with a constant velocity model estimates the relative 3D position and velocity of the intruder. It receives pre-filtered coordinates and derivatives from the detection and radars and uses IMU data to model the egomotion of the interceptor. The planner takes the state estimates as inputs to its policy with the following goals: keeping the intruder in the center of the sensors' field of view, maintaining zero relative horizontal velocity, and ensuring that a given following-distance is held to the target. The planner then outputs body rate and thrust commands which are fed to the drone's flight controller. This ensures that the target is thus followed from below at a safe distance, whatever its flight path may be. Once the interceptor is following the target safely and the operator has requested a catch, the planner reduces its distance to the intruder whilst maintaining it in the center of the field of view and keeping the relative horizontal velocity at zero. Finally, once the relative distance is small enough, a last high thrust command is sent to capture the target by entangling the propellers in the net, thus neutralising the target without damaging it. Once the catch has been completed, the interceptor safely returns to a predesignated location, with the intruder secured in its net.

V. Experimental validation

In parallel with the development of the hardware, the software components were tested in the ROS-compatible physics simulator called Gazebo. Each robotic platform and its sensor module were developed independently. After the initial development in simulation, a series of extensive field experiments were conducted to test each software component and robotic platform. Integration of the entire system was performed in the field. In the following, we report the results of the field experiments and the integration of the developed system.

A. Ground-to-air sensing

The first objective of our mission is to patrol the area and constantly scan to ensure secure airspace. We define an area of interest and plan a waypoint mission on its boundaries, as seen in Fig. 11, to provide better coverage as the probability of detection decreases with the distance from the sensor. We run multiple experiments with the described setup using Skydio 2+ as an intruder (wingspan of 30 cm) and draw some conclusions.

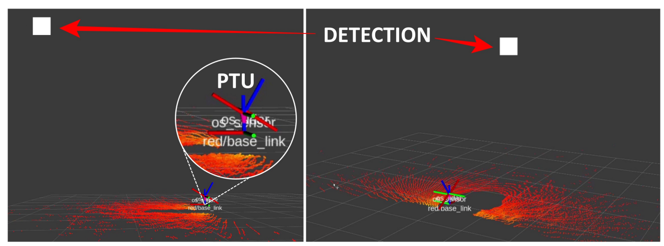

Fig. 6: LiDAR scan

In general, LiDAR scans provide a large amount of high-precision data, but very sparse data, which is especially evident when the objects in the scene are small or further away from the sensor. This is the case with counter-UAS systems which must be able to detect micro-UAVs (wingspan less than 50 cm [23]). To compensate for the gaps between laser beams at a given location, the ground-based LiDAR constantly tilts and scans at different angles. Based on field experiments observations, this has greatly improved our detection probability. In Fig. 6, we can see that the PTU unit with the mounted Ouster sensor is tilted with respect to the base of the patroller UGV, while the point cloud data is transformed into the body frame of the robot. Since we have only one class of objects and assume that everything in the airspace is either known in advance or is a potential candidate for closer inspection, each output of the clustering is a candidate for the pursuer UAV.

Another important aspect for LiDAR-based detection is the reflectivity of an object's surface material. We conduct outdoor field tests comparing two materials on our intruder testbed, one is matte plastic material and the other is aluminium. As expected based on the reflectivity properties of these materials, matte plastic shows lower reflectivity and reduces the likelihood of detection, while aluminium material shows high reflectivity. Since the accuracy of LiDAR-based detection depends on the material properties of the intruder, it is advantageous to couple LiDAR with another modality that is independent of it.

B. Air-to-air inspection

To complement the sparse and accurate detections from ground-based LiDAR sensor, the pursuer UAV is utilizing stereo camera. The stereo camera provides dense RGB-D data at shorter range and requires high computational resources to provide accurate depth measurements. By using a shape-based object representation achieved with synthetically generated data, we can detect the shape of intruder from very far away, resulting in only a few pixels in the image. The detector is capable of detecting intruders even if they occupy only 0.01% of the pixels in the image, which corresponds to a distance of about 30 m for micro UAVs. For this reason, in most experiments we quickly move on to tracking, i.e. we skip the search trajectory around the position reported by LiDAR.

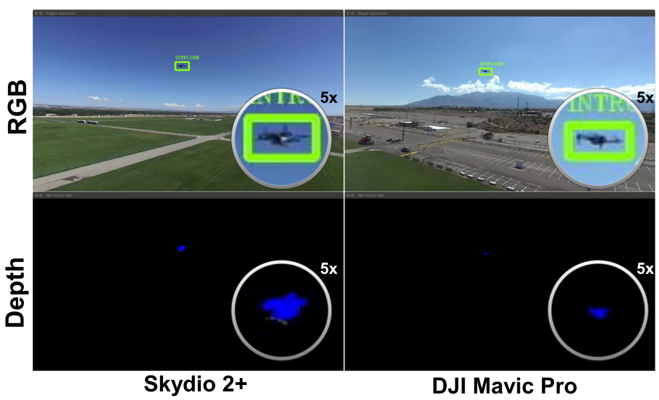

Fig. 7: RGB-D detection from the stereo camera onboard the pursuer UAV. The top row shows the CNN-based detection and the bottom row shows the filtered depth image where the blue pixels represent the selected depth measurements. For both experiments, we use micro UAVs: the Skydio 2+ on the left and the DJI Mavic Pro on the right.

Based on extensive experiments (more than 15 hours of autonomous flight time), we report that we are able to track the intruder moving at up to 2 m/s over and over again. Besides repeatability, the other important feature of air-to-air inspection is the generalisation to different possible UAV models. In the conducted experiments, we alternately use Skydio 2+ and DJI Mavic Pro as intruders. As can be seen in Fig. 7, the developed system is able to detect, inspect, and track the two mentioned micro-UAVs.

C. Mitigation

The refined estimate of the intruders GPS position is used by the interceptor UAV to fly autonomously to a position where it can detect and track the target on its own. Once this is the case the interceptor only relies on its two radars, color camera and IMU to plan body rate and thrust outputs in a local frame. GPS is only used for geofencing. This makes the system robust against GPS drift, since the critical part of following and catching the intruder UAV is independent of GPS and drift of a few meters is acceptable for geofencing as well as for flying below the estimated intruders GPS position. Detection on the RGB data produces a reliable 2D position at a rate of 35Hz. For the follow and catch manoeuvres where the relative distance goes from more than ten meters to zero meters in a short period of time an exact distance estimate is needed from a sensor that can handle different distances as well as changing distance. A single radar can only be in a given configuration, in this case a short-range or a long-range configuration. Using two radars, one in each configuration, enables a longer range and better measurement resolution over the entire combined range. This double-radar setup is able to detect a micro UAV like the DJI Mavic Pro from a distance of half a meter up to a distance of fourteen meters. In field tests this setup was able to follow a DJI Mavic Pro and a Skydio 2+ flying linear and circular trajectories at non-constant speeds whilst keeping a relative distance of seven meters. In eight tests a hovering intruder UAV was successfully caught seven times without causing any additional damage to it.

D. End-to-end mission

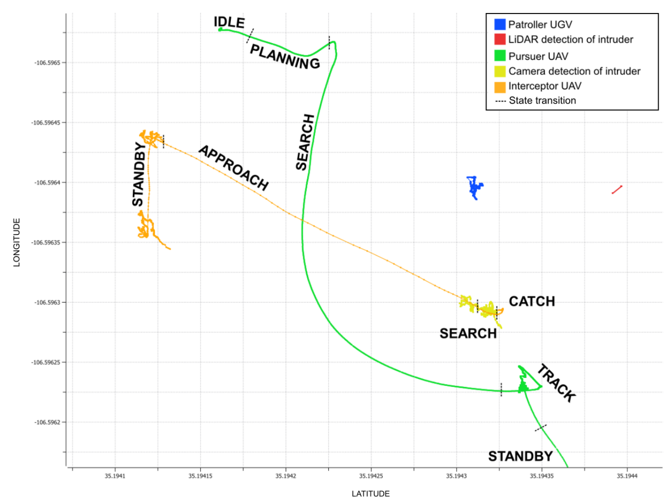

Fig. 8: Trajectories of end-to-end cooperative mission of heterogeneous autonomous multi-robot system.

In this section, we report the results of an end-to-end mission of a heterogeneous cooperative multi-robot system with multi-modal sensing. In preparation for the full cooperative mission, partial integrations were also performed, from patroller UGV to pursuer UAV and from pursuer UAV to interceptor UAV. In the full mission, three different robots operate autonomously and in a distributed manner, cooperating with each other by sharing only essential information. The trajectories of the successful end-to-end mission are shown in Fig. 11. The trajectories of the cooperative robots are reported by GPS, while the trajectory of the intruder is detected by LiDAR and stereo camera. As described earlier, the patroller monitored the area of interest and, once it detected a potential intruder, called the pursuer

UAV for closer inspection and to provide visual feedback to the ground station. The pursuer UAV approached starting position, planned the search trajectory around the reported position, and began searching. As demonstrated in this experiment, the intruder moved during the transition from ground to air sensing. Our system was able to account for this and successfully detect the intruder's new position. The pursuer continuously tracked the intruder and waited for confirmation to proceed. As the operator confirmed from the ground station, the intruder posed a potential risk, therefore the interceptor UAV was deployed to safely retrieve the intruder. The interceptor approached the last known position of the hovering intruder and refined the position information using the fusion of radar and camera measurements. Finally, the interceptor UAV successfully and safely caught the intruder.

VI. Conclusion and future work

In this work, we demonstrated the capabilities of a heterogeneous multi-robot system for cooperative autonomous missions to secure airspace. We developed and integrated multi-modal perception using LiDAR, stereo camera, radar, and monocamera as sensors for detection of multirotor UAVs. We conducted extensive field tests and show that the proposed system is a suitable solution for long-term C-UAS operations with close-range air-to-air inspection and safe mitigation of intruders.

Future work will explore the scaled system with multiple agents of each type. We will also continue to improve the range and speed limits of our system by investigating new hardware options and optimization of the developed algorithms.

Acknowledgments

The authors would like to thank John Ericksen for advice and assistance with the development of the UAV platform and GUI interface, and Jurica Goricanec for assistance with field experiments.

References

[1] R. Mahony, V. Kumar, and P. Corke, "Multirotor aerial vehicles," *IEEE Robotics and Automation magazine*, vol. 20, no. 32, 2012.

[2] A. H. Michel, *Counter-Drone Systems, 2nd ed.* Center for the Study of the Drone at Bard College, December 2019. https://dronecenter.bard.edu/files/2019/12/CSD-CUAS-2nd-Edition-Web.pdf.

[3] J. Ericksen, G. M. Fricke, S. Nowicki, T. P. Fischer, J. C. Hayes, K. Rosenberger, S. R. Wolf, R. Fierro, and M. E. Moses, "Aerial survey robotics in extreme environments: Mapping volcanic co_2 emissions with flocking uavs," *Frontiers in Control Engineering*, vol. 3, pp. 1–13, March 2002.

[4] V. U. Castrillo, A. Manco, D. Pascarella, and G. Gigante, "A review of counter-uas technologies for cooperative defensive teams of drones," *Drones*, vol. 6, no. 3, pp. 1–36, 2022.

[5] J. Wang, Y. Liu, and H. Song, "Counter-unmanned aircraft system (s)(C-UAS): State of the art, challenges, and future trends," *IEEE Aerospace and Electronic Systems Magazine*, vol. 36, no. 3, pp. 4–29, 2021.

[6] H. Kang, J. Joung, J. Kim, J. Kang, and Y. S. Cho, "Protect your sky: A survey of counter unmanned aerial vehicle systems," *IEEE Access*, vol. 8, pp. 168671–168710, 2020.

[7] A. Pierson, Z. Wang, and M. Schwager, "Intercepting rogue robots: An algorithm for capturing multiple evaders with multiple pursuers," *IEEE Robotics and Automation Letters*, vol. 2, no. 2, pp. 530–537, 2016.

[8] Z. Zhou, W. Zhang, J. Ding, H. Huang, D. M. Stipanović, and C. J. Tomlin, "Cooperative pursuit with voronoi partitions," *Automatica*, vol. 72, pp. 64–72, 2016.

[9] D. Shishika, J. Paulos, and V. Kumar, "Cooperative team strategies for multi-player perimeter-defense games," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 2738–2745, 2020.

[10] S. Zhang, M. Liu, X. Lei, P. Yang, Y. Huang, and R. Clark, "Synchronous intercept strategies for a robotic defense-intrusion game with two pursuers," *Autonomous Robots*, vol. 45, no. 1, pp. 15–30, 2021.

[11] V. S. Chipade, V. S. A. Marella, and D. Panagou, "Aerial swarm defense by stringnet herding: Theory and experiments," *Frontiers in Robotics and AI*, vol. 8, p. 81, 2021.

[12] S. Buerger, J. R. Salton, D. K. Novick, R. Fierro, A. Vinod, B. HomChaudhuri, and M. Oishi, "Reachable set computation and tracking with multiple pursuers for the asap counter-uas capability.," tech. rep., Sandia National Lab.(SNL-NM), Albuquerque, NM (United States), 2016.

[13] A. P. Vinod, B. HomChaudhuri, C. Hintz, A. Parikh, S. P. Buerger, M. M. Oishi, G. Brunson, S. Ahmad, and R. Fierro, "Multiple pursuer-based intercept via forward stochastic reachability," in *American Control Conference (ACC)*, pp. 1559–1566, IEEE, 2018.

[14] A. P. Vinod, B. HomChaudhuri, and M. M. K. Oishi, "Forward stochastic reachability analysis for uncontrolled linear systems using Fourier Transforms," in *Proc. of the 20th International conference on Hybrid Systems: Computation and Control*, (Pittsburg, PA, USA), 2017.

[15] P. M. Wyder, Y.-S. Chen, A. J. Lasrado, R. J. Pelles, R. Kwiatkowski, E. O. Comas, R. Kennedy, A. Mangla, Z. Huang, X. Hu, Z. Xiong, T. Aharoni, T.-C. Chuang, and H. Lipson, "Autonomous drone hunter operating by deep learning and all-onboard computations in gps-denied environments," *PLoS ONE*, vol. 14, no. 11, pp. 1–18, 2019.

[16] A. Barisic, M. Car, and S. Bogdan, "Vision-based system for a real-time detection and following of UAV," in *2019 Workshop on Research, Education and Development of Unmanned Aerial Systems (RED UAS)*, pp. 156–159, IEEE, 2019.

[17] A. Barisic and F. P. andStjepan Bogdan, "Brain over brawn: Using a stereo camera to detect, track, and intercept a faster UAV by reconstructing the intruder's trajectory," *Field Robotics*, vol. 2, pp. 222–240, 2022.

[18] M. Vrba and M. Saska, "Marker-less micro aerial vehicle detection and localization using convolutional neural networks," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 2459–2466, 2020.

[19] M. Vrba, D. Heřt, and M. Saska, "Onboard marker-less detection and localization of non-cooperating drones for their safe interception by an autonomous aerial system," *IEEE Robotics and Automation Letters*, vol. 4, no. 4, pp. 3402–3409, 2019.

[20] A. Barisic, F. Petric, and S. Bogdan, "Sim2Air-Synthetic aerial dataset for UAV monitoring," *IEEE Robotics and Automation Letters*, vol. 7, no. 2, pp. 3757–3764, 2022.

[21] M. F. Al-Sa'd, A. Al-Ali, A. Mohamed, T. Khattab, and A. Erbad, "Rf-based drone detection and identification using deep learning approaches: An initiative towards a large open source drone database," *Future Generation Computer Systems*, vol. 100, pp. 86–97, 2019.

[22] F. González, R. Caballero, F. J. Pérez-Grau, and A. Viguria, "Vision-based UAV detection for air-to-air neutralization," in *2021 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)*, pp. 236–241, IEEE, 2021.

[23] "Classification of the unmanned aerial systems." `https://www.e-education.psu.edu/geog892/node/5`, 2022. Accessed: 2022-07-07.