Scalable Coordinated Control of UAV Swarms : A Null Space Behavioral Approach for SAR Missions

1st Alessia Ferraro
DIIES Department
"Mediterranea" University
Reggio Calabria, Italy
alessia.ferraro@unirc.it

2nd Valerio Scordamaglia
DIIES Department
"Mediterranea" University
Reggio Calabria, Italy
valerio.scordamgalia@unirc.it

3rd Francesca Boem
EEE Department
University College of London
London, United Kingdom
f.boem@ucl.ac.uk

***Abstract*—This paper proposes a decentralized priority-based control strategy, employing a Null-Space Behavioral (NSB) approach, to improve the search and rescue (SAR) capabilities of multi-drone systems in post-disaster scenarios. The method ensures scalability and coordination among swarms of UAVs operating in complex 3D environments. Each UAV autonomously adapts its behavior according to a predefined task hierarchy within a fully decentralized architecture designed to maintain efficiency as swarm size increases. The search strategy is structured in three phases: In the first phase, a simultaneous patrol is performed using pre-planned trajectories to cover a large area; in the second phase, the detection mode is activated when a target enters one drone's field of view, followed by an inspection maneuver; and finally, in the third phase after precise localization, the drone alerts the teammates, who converge on the target by performing a dedicated task and position themselves around it to initiate a coordinated identification.**

***Index Terms*—Coordinated Control, UAVs Swarm, Null Space Behavioral Approach, SAR Missions**

I. Introduction

Recent years have seen a marked increase in the frequency of natural disasters, resulting in severe damage to infrastructure and human lives [1], [2]. Urban Search and Rescue (USAR) operations represent the emergency response resulting from the occurrence of such catastrophic events in urban environments [3]. A significant example is represented by the World Trade Center (WTC) disaster [4], [5] which marked the first documented use of mobile robots for USAR operations. The WTC disaster highlighted the unique capabilities of robots in assisting USAR operations, particularly in accessing confined or dangerous areas that would put human rescuers at risk [6]–[9]. Robotic platforms, when equipped with cameras, thermal imaging cameras or hazardous materials detectors, can provide rescue workers with a clear overview of the hazards posed by the disaster environment without posing a danger to human life. For these and other reasons, rescue robotics has been recognized by the National Research Council study "Making the Nation Safer: The Role of Science and Technology in Countering Terrorism" [10] as a critical technology.

In this context, Unmanned Aerial Vehicles (UAVs), commonly known as drones, have emerged as highly effective tools for Search and Rescue (SAR) missions, particularly for rapid scanning of vast disaster areas and for identifying and locating victims [11], [12] . This is crucial for the recovery of survivors in the shortest possible time following natural disasters such as earthquakes, floods or avalanches. Unlike traditional manual SAR operations, which face challenges in identifying human presence and can be time-consuming, UAVs equipped with multimodal sensors, such as high-quality cameras and thermal imaging cameras, can provide aerial imagery to efficiently identify people in need of assistance. The use of a team of multiple UAVs offers an efficient approach to SAR, facilitating coordination, greater scalability, and broader coverage for performing tasks in the shortest possible time, while maximizing the number of survivors rescued. Techniques such as the Layered Search and Rescue (LSAR) algorithm have been proposed for multi-UAV collaboration in SARs, demonstrating improved performance in terms of percentage of survivors rescued and faster rescue times by focusing on the center of the disaster [12]. This problem is often traced back to the problem of multi-robot task allocation (MRTA), or more specifically, multi-UAV task allocation (MUTA), which involves complex coordination challenges. Real-time path planning solutions using cooperative UAVs for SAR missions are also being explored, employing techniques such as optimization for particle swarms within a Model Predictive Control framework to optimize search patterns and maximize the probability of success [13].

Recent advances in Computer Vision (CV) and Machine Learning (ML), particularly Convolutional Neural Networks (CNN) and Deep Learning (DL), are significantly improving the accuracy of human detection from aerial imagery of UAVs for SAR operations [11]. Technologies such as You Only Look Once (YOLO) models, including YOLOv5, are being integrated into UAV systems for real-time monitoring and automatic detection of stranded humans, enabling rescue centers to automatically receive their positions [11], [14].

In addition, intelligent search systems are being developed for autonomous UAVs that can locate and approach people in distress by detecting changes in signal strength, employing genetics-based tracking algorithms for improved tracking accuracy, even in disaster areas where communication with base stations may be disrupted [15].

In line with new trends in the automation of mobile robotic platforms, the authors' goal is to develop a multi-robot system

(MRS) for post-disaster SAR operations, with a focus on the search and location of missing persons. A solution used successfully to coordinate the movements of drone swarms in SAR operations following disasters is the use of a Null-Space Behavioral (NSB) approach [16].

Based on this concept, this paper presents a priority-based decentralized control strategy, employing a Null-Space Behavioral (NSB) approach, to improve the search and rescue (SAR) capabilities of multi-drone systems in post-disaster scenarios. The step forward from the reference work, is to integrate an additional identification phase after target location, allowing the swarm to perform cooperative inspection and classification maneuvers. This improvement increases mission completeness and aligns more closely with real-world SAR requirements. The proposal consists of a decentralized, priority-based control strategy that employs a NSB approach and enables coordinated and scalable control of UAV swarms in which each drone adjusts its behavior based on a task hierarchy in a fully decentralized architecture. The search strategy considers several phases. In a first phase the simultaneous patrolling by UAVs using pre-planned trajectories is performed. A second phase is activated when a target ends up within the cone of view of the drone, which performs an inspection maneuver over the target. Finally, a third phase is carried out when a drone has a clear view of the target, identifying its position.

A. Outline

The document is organized as follows. Sect. II introduces the Null Space Behavioral Approach, while Sect. III reports the mathematical formulation of the tasks selected for application and the mathematical detail of the generation of control actions. Sect. IV presents the description of the state machine-based algorithm. Finally, to evaluate the actual behavior of the vehicles in Search and Rescue (SAR) mission scenarios, Sect. V presents the results of numerical tests performed on the MATLAB environment considering a case study with a patrol scenario involving three UAVs.

PROBLEM FORMULATION AND PROPOSAL

Consider a swarm of N_d flying vehicles, hereinafter labeled as drones, with hover capabilities in a three dimensional space domain $\Psi \in \mathbb{R}^3$. With the goal of searching for survivors of natural disasters, the rescue mission of the N_d units that make up the swarm has been divided into three main phases. In ***Phase 1***, all the UAVs simultaneously patrol different parts of a large area to search for possible survivors. Subsequently, if a suspected survivor is detected by a drone, ***Phase 2*** is activated and the drone gets closer to the potential localized target. Finally in ***Phase 3***, to ensure the dispatch of rescue in the case of actual finding only, drones from neighboring areas, within a predetermined distance, are called out to perform simultaneous identification, and assessment of the target, while avoiding collisions between units. During each of these phases the object tracking convolutional neural network algorithm [14] is used for faster detection of human beings.

A. *Phase 1 - Patrolling*

In the patrolling phase the vast area being searched is divided into smaller zones, each of them assigned to a drone of the swarm. These zones are characterized by the following preliminary assumptions:

i) The domain Ψ is partitioned into N_d disjoint sub-regions, one for each drone, so as to ensure that the region of flight results:

$$\Psi = \bigcup_{i=1}^{N_d} \Psi_i, \tag{1}$$

where $\Psi_i \subset \Psi$ denotes the operational region assigned to the i-th drone.

ii) The sub-regions composing the flight domain are pairwise disjoint such that the following relation applies:

$$\Psi_i \cap \Psi_j = \emptyset \quad \forall i \neq j, \quad i,j \in \{1,\dots,N_d\}, \tag{2}$$

with i and j two different drones.

iii) For each sub-region, a trajectory is defined to perform the patrolling.

$$\mathcal{T} = [\boldsymbol{w}(t_0) \cdots \boldsymbol{w}(t_k) \cdots \boldsymbol{w}(t_\epsilon)]^T, \tag{3}$$

defined as a succession of desired waypoints $\boldsymbol{w}(t) = \{x(t) \;\; y(t) \;\; z(t) \;\; \psi(t)\}$, it's assigned to be followed by the drone to perform the patrolling.

B. *Phase 2 - Detection*

During ***Phase 1***, the drone constantly monitors its surroundings by means of an on-board camera, which is oriented with the same direction. If an object is detected within the field of view of the above-mentioned camera for a relevant number of successive instants, the system abandons the patrol trajectory in favor of a target inspection maneuver. At this point, to reduce the risk of false positives and increase the reliability of detection, in this ***Phase 2***, the drone performs an orbital inspection maneuver around the detected object. This maneuver consists of a circular flight at low angular velocity. The goal is to obtain multiple observations from different angles, improving the quality and comprehensiveness of available visual information. Only at the end of this phase, the object of interest can be subjected to a more advanced identification and assessment phase.

C. *Phase 3 - Identification*

After the ***Detection Phase***, once the possible presence of a survivor is identified within the camera's field of view, the detector drone transmits a signal to other agents operating in nearby regions. This communication includes the estimated position of the target inferred from the detection event. Upon receipt of this information, the remaining drones activate a coordinated response strategy: each drone heads to the circular path around the target, and thanks to the activation of the appropriate tasks, a mutual distance and avoidance of overlapping fields of view are ensured. This configuration not only ensures spatial coverage and redundancy, but also allows the group to maintain visual contact with the target from multiple angles.

II. Preliminaries for Null Space Behavioral Approach

In this paper each UAV is assumed to have on-board control loops that regulate its attitude and altitude. Under this assumption it is supposed that the UAVs composing the swarm can be modeled as material points, therefore the following kinematic model is defined

$$\dot{\boldsymbol{p}}_i(t) = \boldsymbol{u}_i(t), \tag{4}$$

being $\boldsymbol{p}_i(t) = \left[x(t)\ y(t)\ \ z(t)\ \ \psi(t)\right]$ the pose vector, and $\boldsymbol{u}_i(t) = \left[v_x(t)\ v_y(t)\ v_z(t)\ \omega(t)\right]$ the control velocity vector of the i-th drone at time t. The full mission can be accomplished by using M tasks. The m-th task, with $m = 1, \cdots, M$, pertaining to the i-th drone is associated with a cost parameter $\eta_{m,i}$, function of the vehicle pose $\boldsymbol{p}_i$ as follows:

$$\eta_{m,i}(t) = f_m(\boldsymbol{p}_i(t)) \geq 0 \tag{5}$$

with $f_m : \mathbb{R}^3 \to \mathbb{R}$ a continuously differentiable vector valued function.

Assuming that the behavior is is performed if eq. (5) is reduced over time, i.e., $\dot{\eta}_{m,i}(t) \leq 0$, $\forall\, t \geq 0$.

A. Null Space Behavioral Approach Control Scheme

The aim of this contribution is to design a decentralized control solution scalable to a large number of drones, modeled as in eq. (4), that allows to implement the different behaviors to fulfill the prescribed mission described in I. This solution is obtained according to a priority logic. In particular, for each drone, we assume that a **Supervisor** assigns a priority index from 1 to M, function of the drone pose, to each of the implemented behaviors. Consider the following relationship

$$\dot{\eta}_{m,i}(t) = \frac{\partial f_m}{\partial \boldsymbol{p}_i}\dot{\boldsymbol{p}}_i(t) = \boldsymbol{J}_{m,i}(\boldsymbol{p}_i(t)) \cdot \boldsymbol{u}_{m,i}(t), \tag{6}$$

where $\boldsymbol{J}_{m,i}(\boldsymbol{p}_i(t))$ is the Jacobian matrix of f_m. For each behavior, let $\boldsymbol{u}_{m,i}(t)$ be an appropriate feedback control action such that $\dot{\eta}_{m,i}(t) \leq 0$. Each drone must be able to compute an overall control action $\boldsymbol{u}_i(t)$ based on $\boldsymbol{u}_{1,i}, \cdots, \boldsymbol{u}_{M,i}$ that ensures that the highest priority behavior is fully satisfied while the lower priority behaviors are best served [17].

In this work, to guarantee this result, we adopt a Null-Space-Based (NSB) approach, originally introduced in [18], as follows:

$$\boldsymbol{u}_i(t) = \boldsymbol{u}_{1,i}(t) + \sum_{m=2}^{M}\left(\prod_{l=1}^{m-1}\left(\boldsymbol{I} - \boldsymbol{J}^{\dagger}_{l,i}(\boldsymbol{p}_i(t))\boldsymbol{J}_{l,i}(\boldsymbol{p}_i(t))\right)\right)\boldsymbol{u}_{m,i}(t) \tag{7}$$

being $\boldsymbol{u}_{m,i}(t)$ the control action of the i-th unit of the swarm with respect to the m-th task, with $m = 1, \cdots, M$. $\boldsymbol{J}^{\dagger}_{l,i}$ denotes the peusdo-inverse matrix of $\boldsymbol{J}_{l,i}$, and $\boldsymbol{I}$ is the identity matrix. Specifically, for each behavior $m \geq 2$, the control action $\boldsymbol{u}_{m,i}(t)$ is projected into the null space of the Jacobians $\boldsymbol{J}_{l,i}$, with $l = 1, \ldots, m-1$, to ensure that it does not interfere with the fulfillment of higher-priority tasks. This hierarchical structure, illustrated in Fig. 1, allows the execution of multiple behaviors while preserving strict satisfaction of those with highest priority.

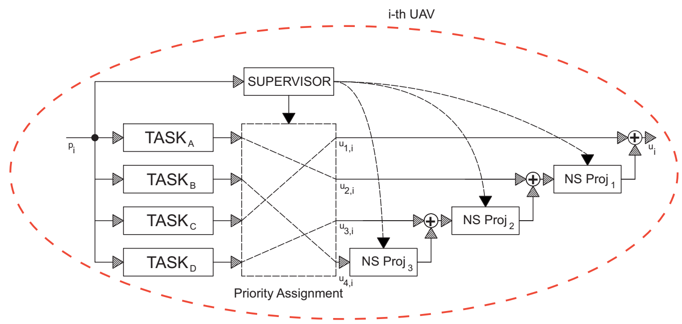

Fig. 1. NSB control scheme. Case $M = 4$. Based on $\boldsymbol{p}_i(t)$, the **Supervisor** assigns priorities. In this case, priority 2 to TASK_A, priority 4 to TASK_B, priority 1 to TASK_C and priority 3 to TASK_D. Based on the priority assignment, the control action is calculated according to the NSB projection.

III. Tasks Mathematical Formulation

To accomplish the mission, the controller of each vehicle incorporates two behaviors, each tasked with different functions:

A) **Guided Navigation Task** : It is the task dedicated to the motion of drones. In particularly, it is used to tracking planned trajectories for patrolling sub-regions in the ***Patrolling Phase*** of the mission, to perform the circular maneuver during the ***Detection Phase***, and to reach the target in the ***Identification Phase***;

B) **Collision-Avoidance Task:** It is the task employed to guarantee a safety distance between the UAV during the ***Identification Phase***;

A. Guided Navigation Task

Let **E** be an inertial reference frame. The following relation is considered:

$$\eta_{GN,i}(t) = \|\boldsymbol{w}(t) - \boldsymbol{p}_i(t)\|_2^2, \tag{8}$$

where $\boldsymbol{w}(t)$ is the desired position at time t, it results that

$$\dot{\eta}_{GN,i}(t) = \boldsymbol{J}_{GN,i}\left(\boldsymbol{p}_i(t)\right) \cdot \left[\dot{\boldsymbol{w}}(t) - \boldsymbol{u}_{GN,i}(t)\right] \tag{9}$$

with

$$\boldsymbol{J}_{GN,i}\left(\boldsymbol{p}_i(t)\right) = 2\left[\boldsymbol{w}(t) - \boldsymbol{p}_i(t)\right]^T. \tag{10}$$

The goal is to make $\dot{\eta}_{GN,i}(t) \leq 0$. To this end, the following control action can be used

$$\boldsymbol{u}_{GN,i}(t) = \dot{\boldsymbol{w}}(t) + \cdot K_{GN}\left(\boldsymbol{w}(t) - \boldsymbol{p}_i(t)\right) \tag{11}$$

being K_{GN} a appropriate proportional control matrix implementing a feedback control law that guarantees the asymptotic stability of the task: when the single task is enabled, the robot asymptotically converges to $\boldsymbol{w}(t)$.

B. Collision Avoidance Task

Consider the generic i-th unit of the swarm, with $i = 1, \cdots, N_d$. For each vehicle l, with $l \neq i$, compute the distance from i. Assuming a minimum safety distance σ_{CA}, the collision avoidance behavior is activated if

$$\|\boldsymbol{p}_l(t) - \boldsymbol{p}_i(t)\|_2 \leq \sigma_{CA} \tag{12}$$

where $|\cdot|_2$ indicates the Euclidean norm.

Let be

$$\eta_{CA,i}(t) = \left(\|\boldsymbol{p}_l(t) - \boldsymbol{p}_i(t)\|_2^2\right) \tag{13}$$

It results that

$$\dot{\eta}_{CA,i}(t) = J_{CA,i}\left(\boldsymbol{p}_i(t)\right) \cdot \left[\dot{\boldsymbol{p}}_l(t) - \boldsymbol{u}_{CA,i}(t)\right], \tag{14}$$

being

$$\boldsymbol{J}_{CA,i}\left(\boldsymbol{p}_i(t)\right) = 2\left(\|\boldsymbol{p}_l(t) - \boldsymbol{p}_i(t)\|_2^2\right) \cdot \left(\boldsymbol{p}_l(t) - \boldsymbol{p}_i(t)\right)^T \tag{15}$$

To achieve $\dot{\eta}_{CA,i}(t) \leq 0$, the following control action can is used

$$\boldsymbol{u}_{CA,i}(t) = \dot{\boldsymbol{p}}_l(t) - \chi_{CA} \cdot K_{CA} \cdot \left(\boldsymbol{p}_l(t) - \boldsymbol{p}_i(t)\right), \tag{16}$$

being K_{CA} an appropriate proportional control matrix which guarantees an increase in distance eq. (12).

IV. Algorithm

The proposed multi-phase behavior is governed by a finite state machine, in which each state corresponds to a specific mission phase. Transitions are triggered by predefined conditions, such as target detection or achievement of the desired configuration. This framework involves a number of operations executed offline on a ground station and a fully decentralized online control phase implemented on each UAV.

-Offline Operations

Given the operational scenario Ψ, the offline phase focuses on pre-processing the data required for real-time execution. The following steps are performed:

1) **Trajectory Planning:** For each UAV and sub-region, the corresponding patrolling trajectory $\mathcal{T}$ is defined using an ad hoc developed trajectory planner.
2) **Data Distribution:** The formation parameters are stored in the on-board memory of each UAV to be used during the online phase.

The control strategy is decentralized and executed independently by each UAV under the following assumptions:

- Each UAV knows its own position $\boldsymbol{p}_i(t)$ in the global reference frame **E**.
- The positions of all other UAVs $\boldsymbol{p}_l(t)$ for $l \neq i$ are accessible.

-Online Operations

The control procedure executed by the i-th UAV varies depending on the current phase of the mission and consists of the following steps.

1) **Task Selection Based on Mission Phase –** The active tasks depend on the operational phase. In particular, three phases are identified:
   - ***Phase 1 - Patrolling***: the active task is the **Guided Navigation Task** with highest priority assigned. It is used to perform the trajectory tracking of the patrol trajectory, using the reference $\boldsymbol{w}(t)$, as defined in eq. (11). As soon as a potential target is detected at position $\boldsymbol{p}(t)$, **Phase 2** is enabled.
   - ***Phase 2 - Detection***: the active task is the **Guided Navigation Task** with highest priority assigned. It is used to perform the trajectory tracking of the circular trajectory, using the reference $\boldsymbol{w}(t)$, which represents the circular path around the position detected in **Phase 1**, as defined in eq. (11).
   - ***Phase 3 - Identification***: Both the **Guided Navigation Task** and the **Collision Avoidance Task** are activated. Priorities are dynamically assigned depending on inter-UAV distances and objective fulfillment.
2) **Collision Check:** At each time step, if there exists at least one UAV $l \neq i$ such that $\|\boldsymbol{p}_l(t) - \boldsymbol{p}i(t)\|_2 \leq \sigma_{CA}$, then the **Supervisor** raises the priority of the **Collision Avoidance** task to the highest level.

   Remark - In the case where several units are at a distance less than the threshold σ_{CA}, it will be necessary to replicate this behavior for each of the possible couples. The resulting actions will be ordered by priority function of the distance between the units.
3) **Control Action Synthesis:** The control input is computed according to eq. (7), ensuring strict compliance with the highest priority task and optimal fulfillment of lower-priority tasks.

This decentralized scheme guarantees conflict-free behavior arbitration, allowing the UAVs to react in real-time to dynamic changes in the environment and team configuration while respecting mission priorities. For more details, see Fig. 2.

V. Numerical Results

To evaluate the effectiveness of the proposed strategy for coordinated control of the UAVs swarm, several simulations were carried out in the MATLAB environment modeling a swarm of drones operating in a bounded 3D environment.

The area considered for each sub-region Ψ_i measures approximately $200 \times 100 = 20000\text{m}^2$. The area was initially discretized with a virtual grid Φ used to perform the ***Patrolling Phase***. The desired altitude for patrolling was set to 20m. During the ***Patrolling Phase***, each drone successfully covered its assigned subregion, following the predefined trajectory and keeping the recognition algorithm active. We assume that no multiple targets are present in the same inspection area, and no targets are present in neighboring areas. At the time of detection, the transition from ***Patrolling Phase*** to the ***Detection Phase*** was activated and the detector drone performed as expected the circular inspection maneuver at

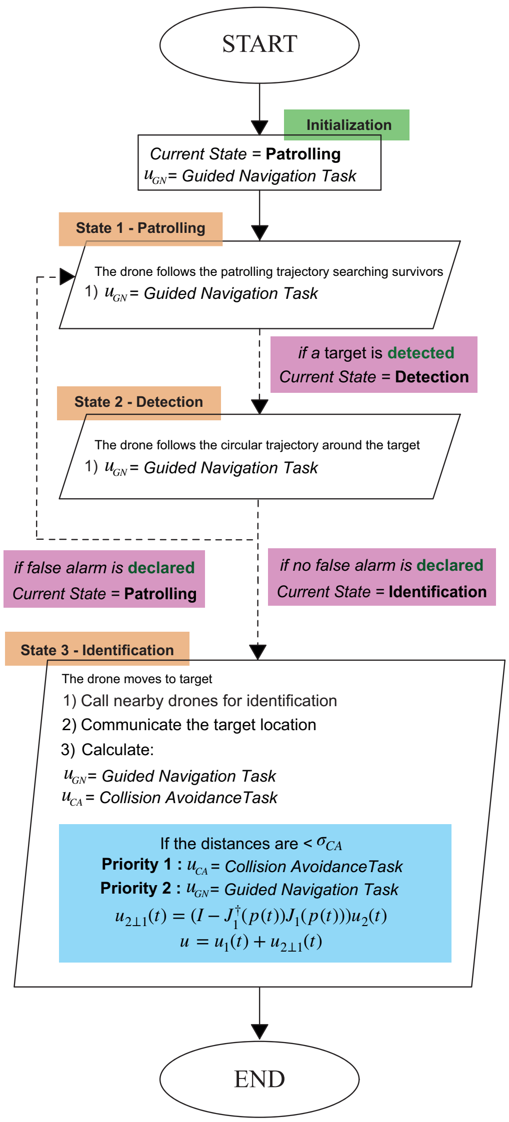

Fig. 2. Algorithm flowchart.

the prescribed altitude and rotational speed $\omega = 5$deg/s, acquiring multi angle views of the potential target. Once the detection was validated, the ***Identification Phase*** was activated. The detector drone transmitted the estimated target position information to the swarm. Meanwhile, the remaining drones began their approach to the target. During this phase, collision avoidance was effectively ensured by activating the **Collision Avoidance Task** when the distances between drones fell below the predefined threshold $\sigma_{CA} = 10$m.

The considered case presents a swarm consisting of $N_d = 3$ UAVs. In this case study, the random position of the target was found to be equal to $x_T = 26.4166$m and $y_T = 72.2725$m. The camera orientation was set in line with the direction of the drone during the ***Patrolling Phase***, while for the ***Detection Phase*** and ***Identification Phase*** it was set in the direction of the target. A FOV of 90deg was used throughout the simulation. The results obtained are shown in Figs. 3-5.

In Fig. 3 the poses of the three drones during the whole simulation, focusing on the area patrolled by UAV #1, are shown. During the ***Patrolling Phase*** the UAV#1 follows the planned trajectory for complete coverage of the area. After an initial detection, the ***Detection Phase*** is activated and UAV#1 performs the orbital maneuver around the possible target, using the estimated position of the target as its center. It then enters in the ***Identification Phase***. The other two drones begin to converge toward the target to perform the multi-angle measurements and make the actual identification.

Fig. 4 shows the mutual distances recorded between the drones during the ***Identification Phase*** of the mission.

Finally, the control variables for the three drones during the mission performance are shown in Fig. 5.

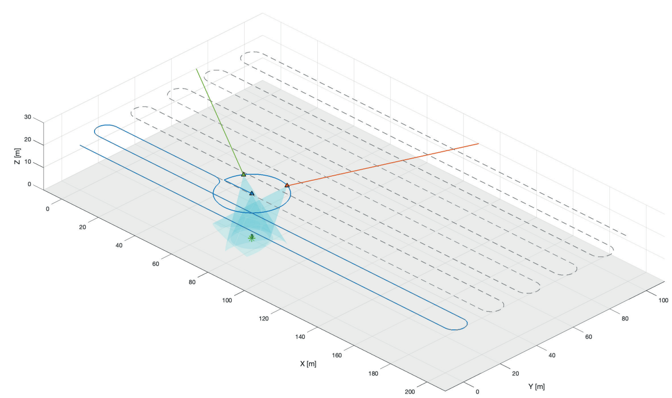

Fig. 3. Patrolling sub-area assigned to UAV #1: pose of UAV#1, UAV#2, and UAV#3. The dashed black line represents the planned patrol trajectory, while the solid blue line represents the trajectory executed by UAV#1. After a first detection the UAV#1 makes a turn around the possible target, and subsequently, the other drones start to approach. The trajectories for UAV#2 and UAV#3 are represented by the green and orange solid lines, respectively. The light blue cones represent the sensor field of view, while the detected survivor is indicated by the green parallelepiped. The gray area on the X-Y plane represents the surveilled surface.

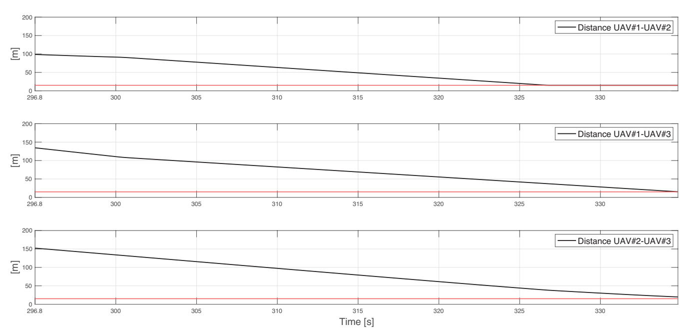

Fig. 4. Mutual distances recorded between UAV#1, UAV#2 and UAV#3 during the simulation. Each subplot shows the temporal evolution of the distance between a specific pair of drones: UAV#1-UAV#2 (top), UAV#1-UAV#3 (middle) and UAV#2-UAV#3 (bottom). The horizontal red line indicates the predefined safety threshold σ_{CA}.

VI. Conclusions

In this paper is presented a priority-based decentralized control strategy, employing a Null-Space Behavioral (NSB)

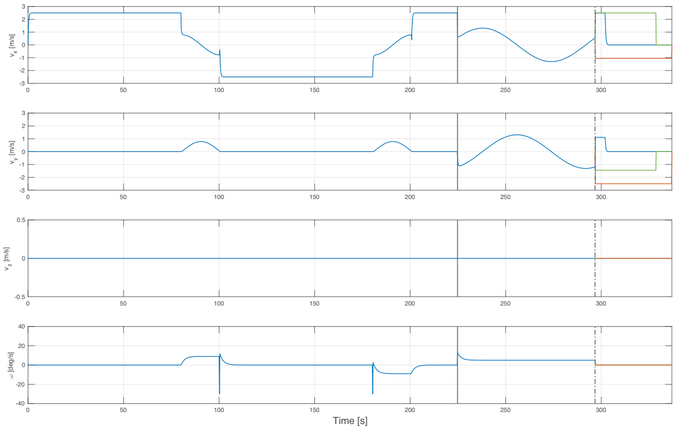

Fig. 5. Temporal evolution of control inputs in longitudinal v_x, lateral v_y, vertical v_z speeds, and angular velocity ω for the three drones UAV#1, UAV#2, and UAV#3 represented by the solid blue, solid green, and solid orange lines, respectively. The vertical lines indicate key moments in the simulation: the solid black line marks the start of the ***Detection Phase***, while the dotted black line marks the start of the ***Identification Phase***. The control variables for UAV#2 and UAV#3 are only shown in relation to this phase in which they are actually active.

approach, to improve the search and rescue (SAR) capabilities of multi-drone systems in post-disaster scenarios. The solution presented is scalable for the coordinated control of swarms of UAVs operating in complex three-dimensional environments with no-fly zones and obstacles. Each UAV dynamically adapts its behavior according to a predefined task hierarchy. The control architecture is fully decentralized and designed to maintain performance and scalability as the number of UAVs increases. The search strategy is divided into three phases: (i) simultaneous patrolling along predefined trajectories for efficient area coverage; (ii) target detection and inspection when a subject enters a drone's field of view; (iii) cooperative identification, where the detecting UAV communicates the exact target position and the swarm converges around it. To demonstrate the effectiveness of the proposed solution, tests were carried out on a MATLAB simulation environment considering a swarm composed of three UAVs. The test results demonstrated the collision avoidance and coordination capabilities between the members of the swarm.

Acknowledgment

This work was supported by the research project - ID:P2022XER7W "CHEMSYS: Cooperative Heterogeneous Multi-drone SYStem for disaster prevention and first response" granted by the Italian Ministry of University and Research (MUR) within the PRIN 2022 PNRR program, funded by the European Union through the PNRR program.

Finanziato dall'Unione europea
NextGenerationEU

MUR

Italiadomani

References

[1] R. R. Murphy, *Disaster robotics*. MIT press, 2014.

[2] A. Ferraro, V. Nardi, E. D'Amato, I. Notaro, and V. Scordamaglia, "Multi-drone systems for search and rescue operations: problems, technical solutions and open issues," in *2023 IEEE International Workshop on Technologies for Defense and Security (TechDefense)*. IEEE, 2023, pp. 159–164.

[3] R. R. Murphy, "Human-robot interaction in rescue robotics," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 34, no. 2, pp. 138–153, 2004.

[4] J. Casper and R. R. Murphy, "Human-robot interactions during the robot-assisted urban search and rescue response at the world trade center," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 33, no. 3, pp. 367–385, 2003.

[5] M. MACIRE, "Analysis of robotic platforms used at the world trade center disaster," *PhD thesis, MS thesis, Department of Computer Science and Engineering, University of South Florida*, 2002.

[6] A. Birk, B. Wiggerich, H. Bülow, M. Pfingsthorn, and S. Schwertfeger, "Safety, security, and rescue missions with an unmanned aerial vehicle (uav) aerial mosaicking and autonomous flight at the 2009 european land robots trials (elrob) and the 2010 response robot evaluation exercises (rree)," *Journal of Intelligent & Robotic Systems*, vol. 64, pp. 57–76, 2011.

[7] E. Bitton and K. Goldberg, "Hydra: A framework and algorithms for mixed-initiative uav-assisted search and rescue," in *2008 IEEE International Conference on Automation Science and Engineering*. IEEE, 2008, pp. 61–66.

[8] M. Erdelj and E. Natalizio, "Uav-assisted disaster management: Applications and open issues," in *2016 international conference on computing, networking and communications (ICNC)*. IEEE, 2016, pp. 1–5.

[9] D. Erdos, A. Erdos, and S. E. Watkins, "An experimental uav system for search and rescue challenge," *IEEE Aerospace and Electronic Systems Magazine*, vol. 28, no. 5, pp. 32–37, 2013.

[10] N. R. Council, D. on Engineering, P. Sciences, C. on Science, and T. for Countering Terrorism, *Making the nation safer: The role of science and technology in countering terrorism*. National Academies Press, 2002.

[11] A. A. B. Abdelnabi and G. Rabadi, "Human detection from unmanned aerial vehicles' images for search and rescue missions: A state-of-the-art review," *IEEE Access*, 2024.

[12] E. T. Alotaibi, S. S. Alqefari, and A. Koubaa, "Lsar: Multi-uav collaboration for search and rescue missions," *IEEE Access*, vol. 7, pp. 55 817–55 832, 2019.

[13] F. A. de Alcantara Andrade, A. Reinier Hovenburg, L. Netto de Lima, C. Dahlin Rodin, T. A. Johansen, R. Storvold, C. A. Moraes Correia, and D. Barreto Haddad, "Autonomous unmanned aerial vehicles in search and rescue missions using real-time cooperative model predictive control," *Sensors*, vol. 19, no. 19, p. 4067, 2019.

[14] M. Sruthi, M. J. Poovathingal, V. Nandana, S. Lakshmi, M. Samshad, and V. Sudeesh, "Yolov5 based open-source uav for human detection during search and rescue (sar)," in *2021 International Conference on Advances in Computing and Communications (ICACC)*. IEEE, 2021, pp. 1–6.

[15] D. Oh and J. Han, "Smart search system of autonomous flight uavs for disaster rescue," *Sensors*, vol. 21, no. 20, p. 6810, 2021.

[16] M. Buonsanti, E. D'Amato, A. Ferraro, I. Notato, and V. Scordamaglia, "Task priority approach for solving coordination of moving mobile robot in sar operations," in *2024 IEEE International Workshop on Technologies for Defense and Security (TechDefense)*. IEEE, 2024, pp. 474–479.

[17] G. Antonelli, F. Arrichiello, and S. Chiaverini, "Experiments of formation control with collisions avoidance using the null-space-based behavioral control," in *2006 14th Mediterranean Conference on Control and Automation*. IEEE, 2006, pp. 1–6.

[18] G. Antonelli, F. Arrichiello, S. Chakraborti, and S. Chiaverini, "Experiences of formation control of multi-robot systems with the null-space-based behavioral control," in *Proceedings 2007 IEEE international conference on robotics and automation*. IEEE, 2007, pp. 1068–1073.