PACNav: Enhancing Collective Navigation for UAV Swarms in Communication-Challenged Environments

Afzal Ahmad[1], Daniel Bonilla Licea[1,2], Giuseppe Silano[1], Tomas Baca[1], and Martin Saska[1]

***Abstract*— This article presents Persistence Administered Collective Navigation (PACNav) as an approach for achieving decentralized collective navigation of Unmanned Aerial Vehicle (UAV) swarms. The technique is inspired by the flocking and collective navigation behavior observed in natural swarms, such as cattle herds, bird flocks, and even large groups of humans. PACNav relies solely on local observations of relative positions of UAVs, making it suitable for large swarms deprived of communication capabilities and external localization systems. We introduce the novel concepts of path persistence and path similarity, which allow each swarm member to analyze the motion of others. PACNav is grounded on two main principles: (1) UAVs with little variation in motion direction exhibit high path persistence and are considered reliable leaders by other UAVs; (2) groups of UAVs that move in a similar direction demonstrate high path similarity, and such groups are assumed to contain a reliable leader. The proposed approach also incorporates a reactive collision avoidance mechanism to prevent collisions with swarm members and environmental obstacles. The method is validated through simulated and real-world experiments conducted in a natural forest.**

I. Full-version

A full version of this work is available at `https://iopscience.iop.org/article/10.1088/1748-3190/ac98e6`. To reference, use [1].

II. Introduction

The use of a group of UAVs can reduce mission time and provide the redundancy and safety that is critical in many real-world applications [2]. However, employing a centralized system to control the motion of all the UAVs in the swarm can be challenging due to the unavailability of reliable and real-time information about the environment and other UAVs in the swarm. Animals, like fish and birds, serve as prime examples of multi-agent systems that employ decentralized decision-making for collective motion [3], [4]. For instance, [4] draw insights from animal motion to devise a set of simple rules addressing attraction and repulsion to neighbors and alignment with the group, enabling collective motion. In many cases, decentralized decision-making systems rely solely on local information about neighbors, making these methods scalable to a large number of robots.

This paper introduces a bioinspired decentralized approach for the collective navigation of a swarm of UAVs, leveraging onboard sensor data for control without reliance on Global Navigation Satellite System (GNSS) or communication. By demonstrating UAVs navigating effectively through a forest environment, the approach challenges the stereotype of swarms being limited to "toy scenarios," highlighting their potential for real-world applications. Drawing from collective motion analysis in animal and human groups, *path similarity* and *path persistence* metrics are designed to compare UAV trajectories. Individual UAVs follow a target UAV selected based on these metrics, enabling collective motion. Emphasizing safety, the collision avoidance mechanism is tailored for complex real-world environments. Both simulated experiments and real-world flights in natural forest environments validate and analyze the approach's performance and robustness. The related source code has been released as open-source[1].

III. Problem Description

We address the challenge of navigating a UAV swarm, which lacks communication and global localization capabilities, within an environment containing randomly distributed obstacles. The objective of the swarm is to collectively advance towards a goal location known only to a subset of the UAVs. Navigation relies on on-board sensors for mapping and localizing obstacles and other UAVs within the environment.

IV. Problem Solution

We introduce a decentralized control method for UAVs that rely solely on onboard sensors and computational resources to govern their motion. As the movement of each UAV is influenced by the motion of others in the swarm, collective navigation emerges through the control of individual UAVs. Our method comprises of two phases: In the first phase, each UAV determines a suitable target UAV to follow, and in the second phase, it computes motion control commands to reach the target while avoiding collisions with obstacles and other UAVs.

During the first phase, at each time instant k, the i-th UAV selects a target location $\mathbf{d}_i[k] \in \mathbb{R}^2$ and plans a path to reach it. This target can either be the goal position $\mathbf{g}$ if the UAV belongs to the informed subgroup or a neighboring UAV potentially moving towards the goal $\mathbf{g}$. To select this target, we generate a set of potential targets $\mathcal{T}_i[k]$, considering three

[1]Afzal Ahmad, Daniel Bonilla Licea, Giuseppe Silano, Tomas Baca, and Martin Saska are with the Department of Cybernetics, Czech Technical University in Prague, 12135 Prague, Czech Republic (email: `name.surname@fel.cvut.cz`).

[2]Daniel Bonilla Licea is with the college of Computing, Mohammed VI Polytechnic University, Ben Guerir, Morocco (email: `daniel.bonilla@um6p.ma`).

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[1]`https://github.com/ctu-mrs/pacnav`

criteria: (i) *UAVs not in close proximity*: UAVs close to the i-th UAV are mostly influenced by the collision avoidance mechanisms, so only those beyond a certain distance are considered; (ii) *UAVs not moving towards the previous target position* $\mathbf{d}_i[k-1]$: UAV in moving towards the previous target are excluded; (iii) *UAVs with sufficient path history* $\mathbf{H}_{ij}[k]$[2]: Targets must have a path of at least three elements for path persistence analysis.

In the second phase, if the UAV does not belong to the informed subgroup, it selects a target $\mathbf{d}_i[k]$ based on path similarity (σ_{ijl}) and persistence (γ_{ij}) metrics. Specifically, it chooses a target $j^\star$ from $\mathcal{T}_i[k]$ by maximizing a combined metric of path persistence and similarity. Thus, we can express this as:

$$\mathbf{d}_i[k] = \Big[\mathbf{H}_{ij^\star}[k]\Big]_1, \tag{1}$$

with

$$j^\star = \underset{j \in \mathcal{T}_i[k]}{\operatorname{argmax}} \left(\gamma_{ij} + \sum_{l \in \mathcal{T}_i[k] \setminus j} \sigma_{ijl} \right). \tag{2}$$

Once the target is selected, the UAV computes a path to it while avoiding obstacles and other UAVs. This is achieved by controlling the UAV velocity, denoted as $\mathbf{u}_i$, which is the sum of navigation and collision avoidance vectors:

$$\mathbf{u}_i[k] = \mathbf{n}_i[k] + \mathbf{c}_i[k], \tag{3}$$

where the navigation vector $\mathbf{n}[k]$ is determined by the UAV's informed status and proximity to neighbors. It guides the UAV towards the desired target while maintaining cohesion with the swarm. On the other hand, the collision avoidance vector $\mathbf{c}[k]$ is a combination of vectors aimed at avoiding obstacles. It responds more assertively to nearby obstacles and is designed to ensure smooth motion.

In the rest of this section, we explain the process from the UAV's perspective, and to simplify the notation, we drop the subscript i from $\mathbf{n}_i[k]$ and $\mathbf{c}_i[k]$ variables. The navigation vector $\mathbf{n}[k]$ is given by:

$$\mathbf{n}[k] = f_{ig}\mathbf{n}_I + \bar{f}_{ig}\mathbf{n}_U, \tag{4}$$

where $f_{ig} = 1$ if, and only if, the UAV has goal information, while $\bar{f}_{ig}$ is its complementary function. The vector $\mathbf{n}_I$ is used if the UAV is informed about the goal and is calculated as

$$\mathbf{n}_I = \max\left(V^m, 1 - \frac{\sum_{j \in \mathcal{N}_i} \|\check{\mathbf{p}}_{ij} - \mathbf{p}_i\|}{2R^f|\mathcal{N}_i|} \right) K^n(\mathbf{a}_n - \mathbf{p}_i), \tag{5}$$

where, $\mathcal{N}_i$ is the set of neighboring UAVs, $V^m \in (0,1)$ is the minimum normalized velocity of the informed UAV, and $K^n \in \mathbb{R}$ is a scaling coefficient to rescale the position vector to form the velocity control input ($\mathbf{u}_i[k]$). The second term in the $\max$ function depends on the average distance from the UAVs in $\mathcal{N}_i$. The magnitude of vector $\mathbf{n}_I$ decreases as this average distance increases, preventing the informed UAV from wandering far away from the swarm. The $\max$ function ensures that the UAV always moves with a minimum velocity of V^m.

The collision avoidance vector for an obstacle $\mathbf{o}_r \in \mathcal{O}_i[k]$ is obtained by:

$$\mathbf{c}_r = \max\left(0, \frac{1}{\|\mathbf{p}_i - \mathbf{o}_r\|} - \frac{1}{R^o}\right)\hat{\mathbf{c}}_r, \tag{6}$$

with

$$\hat{\mathbf{c}}_r = \underset{\hat{\mathbf{b}} \in \{\hat{\mathbf{c}}^+, \hat{\mathbf{c}}^-\}}{\operatorname{argmax}} \left(\frac{\hat{\mathbf{b}} \cdot \mathbf{u}_i[k-1]}{\|\mathbf{u}_i[k-1]\|} \right), \tag{7}$$

where vectors $\hat{\mathbf{c}}^+$ and $\hat{\mathbf{c}}^-$ denote two possible directions of motion to avoid collision with the obstacle $\mathbf{o}_r$. To maintain smooth motion, the vector with the least angular distance to the previous control input $\mathbf{u}_i[k-1]$ is used for collision avoidance. The magnitude of $\mathbf{c}_r$ is inversely proportional to the relative distance to the obstacle, meaning that the UAV reacts more strongly to nearby obstacles compared to farther ones. The collision control vector $\mathbf{c}[k]$ is a superposition of collision avoidance vectors of all the obstacles in $\mathcal{O}_i[k]$, given by:

$$\mathbf{c}[k] = K^c \sum_{\mathcal{O}_i[k]} \mathbf{c}_r, \tag{8}$$

where K^c is a scaling coefficient to rescale the summation.

V. Experimental Results

We evaluated the performance of the proposed approach through simulated experiments using Gazebo and field experiments conducted in a natural forest. Videos showcasing these experiments are accessible at `https://mrs.felk.cvut.cz/pacnav`. Refer to [5], [6] for additional information regarding the hardware and software used for the experiments.

References

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[2]It is worth noting that the proposed approach relies on a sequence of UAV position estimates stored in the matrix $\mathbf{H}_{ij}[k]$, referred to as the path history matrix. Further details about the structure and algorithms for the update can be found in [1]