Sensing Testbed: Decentralized Drone Coordination with Swarm Intelligence and Collision Avoidance

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1 INTRODUCTION

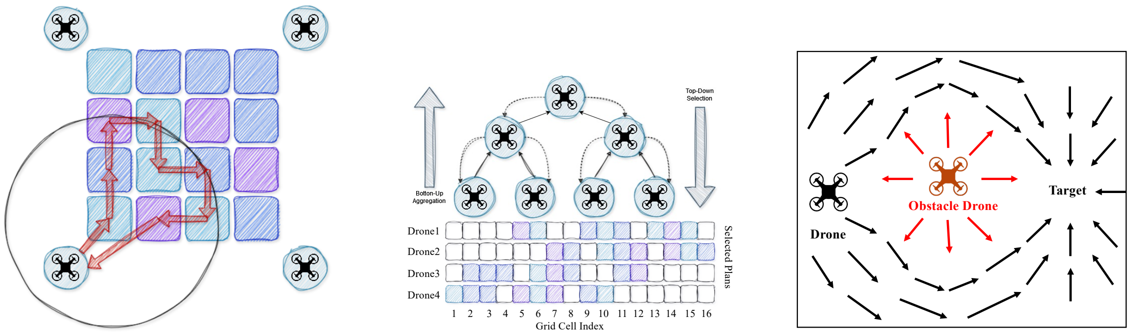
Unmanned Aerial Vehicles (UAVs), referred to as drones, can organize themselves into swarms, fostering collaboration and efficiency in sensor data collection within Smart Cities Butilă & Boboc (2022). With their mobility, autonomy, and diverse sensors, drones have been widely used in the transportation systems. For instance, drones can be used for an accurate monitoring of traffic to detect traffic congestion at early stage. This allows traffic operators to apply mitigation actions that decrease the carbon footprint of a sector with one of the highest carbon emissions worldwide Barmpounakis & Geroliminis (2020).

Utilizing multiple low-cost drones over a wide sensing area offers a flexible alternative to single high-profile drones. They complete sensing missions in parallel, benefiting from shorter recharging times. This requires coordinated actions with autonomy and computational intelligence Poudel & Moh (2022). Recent advancements in decentralized optimization and multi-agent learning algorithms offer scalability and efficiency while maintaining privacy and autonomy Chen *et al.* (2022), Qin & Pournaras (2023). However, developing, testing, and evaluating such solutions is complex. Simulation environments simplify studying swarm intelligence and collision avoidance algorithms by reducing complexity and environmental variables. In contrast, real-world drone experiments indoors and even outdoors enhance realism and external validity.

To bridge this gap, this paper introduces a testbed to study distributed sensing problems of drones, such as such as energy consumption, charging control, navigation and collision avoidance. This testbed sets a stepping stone to emulate, within small laboratory spaces, large sensing areas of interest originated from empirical data and simulation models. As a proof-of-concept, a multi-agent collective learning approach Pournaras *et al.* (2018), Pournaras (2020) is applied to this testbed to coordinate and optimize in a fully decentralized way the navigation and sensing of drones. Furthermore, a potential field collision avoidance method is applied to predict the fields of collisions and finds the optimal flying trajectories of drones to mitigate the risk of collisions and sensing inefficiency. Extensive experimentation using real-world data in traffic monitoring in Athens city Barmpounakis & Geroliminis (2020) validates the efficiency in traffic vehicle observation, demonstrating the capacity of the testbed to move complex swarm intelligence and collision avoidance algorithms for drones to real-world.

2 METHODOLOGY

The proposed testbed relies on a model, which can be implemented in different lab environments. At an abstract level, the testbed is modeled by the elements presented in the rest of this section.



(a) The sensing map in grid cells and a possible plan (or path) of a drone. The circles represent base stations.

(b) Optimized plan selection of navigation and sensing using EPOS collective learning Pournaras *et al.* (2018)

(c) Collision avoidance with PFG. The black vectors show directions to target for the drone and avoid the obstacle drone.

Figure 1 – *A prototype of drones testbed for indoor sensing lab using both collective learning and potential field collision avoidance approaches.*

Drones. They communicate to interact with each other directly or via proxies. They run software that implements swarm intelligence for distributed sensing. Each drone can run its swarm intelligence software within the following continuum Fanitabasi *et al.* (2020): (i) offline/online, remote, centralized computations (server), and (ii) online, locally on drones, distributed computations.

Sensing map. It is a 2D map over the spatial illustrative model where drones perform sensing, shown in Figure 1(a). In this scenario, a finite number of base/charging stations, from where drones depart and return, are set with fixed coordinates in the area. Besides, given a number of points of interest, each is regarded as a grid cell that covers an area in the map. In the context of a sensing task, each cell at a time period has specific sensing requirements that determine data acquisition of drones. A higher sensing requirement in a cell represents a more urgent for traffic monitoring over this area (e.g., the accidents or crucial intersection of traffic flow). Thus, a higher number of sensing values is set at this cell, which requires drones to hover a longer time over the cell to measure accurately. We assume the number of observed vehicles as the required sensing values.

Swarm intelligence. It plans in a coordinated way the navigation and sensing of multiple drones such that each self-select one plan (or a path) influenced by the selections of others. As a result, the total sensing by the swarm matches well the sensing requirements of all cells. This matching represents the relative approximation between the total sensed values per cell and the actual sensing requirements per cell. Error and correlation metrics such as the root mean squared error, cross-correlation or residuals of summed squares can estimate this matching Pournaras (2020).

Collision avoidance. It is commonly used in robotics, that creates force to repel robots from obstacles and attract them towards their goal. In this implementation, a dynamically sized Potential Fields Grid (PFG) is created to the drone positions' scale, travel distance per timestamp, and minimum safe distance between drones to prevent collisions Sun *et al.* (2017). As shown in Figure 1(c), a PFG is a 2D-grid of vectors created for each drone, where each vector points in the direction the drone should fly at that position per timestamp.

3 RESULTS

3.1 Testbed prototyping

(a) The Crazyflie 2.1, a versatile open source flying development platform that only weighs 27g.

(b) Indoor sensing environment using screen displaying the traffic vehicles.

(c) A swarm of drones hovering over the central business district of Athens with 10 grids to record traffic flows.

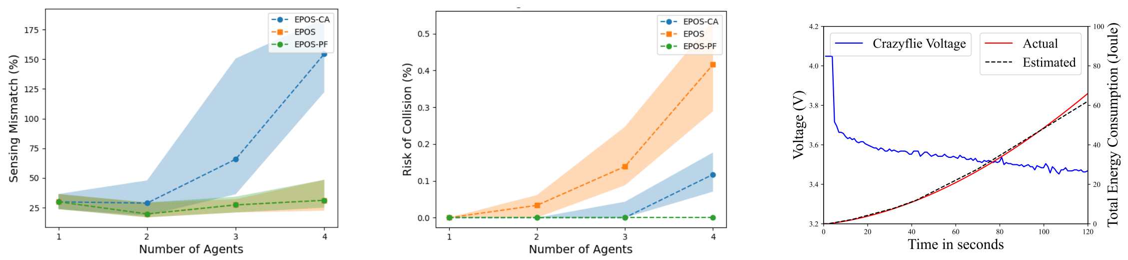
Figure 2 – *The prototyped testbed built with Crazyflies, big screen and pNEUMA dataset.*

This testbed uses the Crazyflie 2.1, shown in Figure 2(a), because of its size, weight and accessibility [1]. This drone can be programmed in Python, and multiple Crazyflies can fly for swarm applications. Crazyflie 2.1 can be mounted by multiple hardware decks to support different functions, such as camera, positioning, and wireless charging. Besides, we set a 75 inch screen on the ground as an indoor map to emulate the outdoor sensing environments, shown in Figure 2(b). The screen displays the video recorded from the satellite such that Crazyflies can observe the traffic flow of vehicles. To show the significant and broad impact of the testbed on a transportation scenario, we choose the congested downtown area of Athens in Figure 2(c), where a swarm of drones hovering to record traffic streams of vehicles Barmpounakis & Geroliminis (2020). During the coordinated plan selection via EPOS[2], agents (or drones) self-organize into a balanced binary tree as a way of structuring their learning interactions. The shared goal of the agents is to minimize the sensing mismatch, i.e., the residual sum of squares (RSS) between the total number of vehicles observed by drones and the total number of vehicles acquired from pNEUMA [3], both in unit-length scaled. More information about EPOS is out of the scope of this paper and can be found in earlier work Pournaras *et al.* (2018), Pournaras (2020).

3.2 Experimental Evaluation

We measure the sensing mismatch and the risk of collisions (i.e., the traveling distance that drones are easy to collide divided by the total traveling distance) Candan (2021) using EPOS with and without potential field collision avoidance, named *EPOS-PF* and *EPOS* respectively. We also use EPOS with traditional Collision Avoidance, named *EPOS-CA*, as a baseline method. In this method, drones with lower-priority sensing tasks are instructed to wait until those with higher-priority complete their missions. Figure 3(a) and 3(b) illustrate that the proposed *EPOS-PF* achieves significantly high sensing quality while mitigating the risk of collisions. Figure 3(c) illustrates the real-time voltage of LiPo battery used in Crazyflie as well as corresponding actual energy consumption during the mission. It proves the accurate model-based estimated energy consumption, which further validates the applicability and realism of the testbed.

[1]https://www.bitcraze.io/products/crazyflie-2-1/
[2]EPOS is open-source and available at: https://github.com/epournaras/EPOS.
[3]https://open-traffic.epfl.ch/



(a) *EPOS-PF* significantly decreases sensing mismatch compared to *EPOS-CA*.

(b) *EPOS-PF* significantly prevents the risk of collisions compared to *EPOS*.

(c) Comparison between accurate and estimated energy consumption.

Figure 3 – *Performance comparison of the proposed method and baseline methods in sensing mismatch, risk of collisions and energy consumption.*

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