FireHunter: Toward Proactive and Adaptive Wildfire Suppression via Multi-UAV Collaborative Scheduling

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***Abstract*—Multi-robot systems are adept at handling complex tasks in large-scale, dynamic, and cold-start scenarios such as wildfire control. This paper introduces *FireHunter* to tackle the challenge of coordinating fire monitoring and suppression tasks simultaneously in unpredictable environments. *FireHunter* utilizes a confidence-aware assessment method to identify optimal locations and a priority graph-based algorithm to coordinate robots efficiently. It effectively manages the dynamic planning inclinations for sensing and operational tasks, ensuring real-time information collection and timely environmental intervention. Experimental results from simulation show that *FireHunter* reduces fire expansion ratio by 59% compared to state-of-the-art solutions.**

***Index Terms*—Multi-robot System, Collaborative Sensing**

I. Introduction

Wildfires pose severe threats, causing extensive damage to human life, homes, infrastructure, and ecosystems [1]. The 2020 California wildfires alone burned 4 million acres, leading to substantial financial losses and environmental consequences. Conventional firefighting methods face limitations in large-scale and dynamic scenarios due to slow mobility, challenging terrain, and cost constraints of manned aircraft. Unmanned Aerial Vehicles (UAVs) offer promising solutions, being mobile, equipped with sensors for real-time information capture, and cost-effective [2]. Their agility allows access to challenging areas, aiding in identifying hotspots and optimizing firefighting resource allocation [3]–[5].

Given the unpredictable nature of environmental factors like wind, which can quickly change the size, location, and shape of fires, certain regions within the operational zone may become unpredictable at specific times, necessitating re-evaluation of these areas when their status is uncertain. Therefore, scheduling for wildfire monitoring and suppression tasks should be conducted concurrently – inadequate monitoring may lead to suboptimal positioning for effective firefighting efforts. Conversely, insufficient suppression efforts could exacerbate fire dynamics.

Our Work aims to develop an efficient approach for coordinating the activities of multiple UAVs to simultaneously carry out wildfire monitoring and suppression in large-scale and dynamic wildfires, as shown in Fig. 1. Specifically, we concentrate on scenarios where a limited number of robots are deployed in emergency situations, often with little prior knowledge of the environment. We introduce *FireHunter*, a collaborative framework for scheduling multiple UAVs to perform integrated wildfire monitoring and suppression. *FireHunter* dynamically assesses the wildfire situation and adjusts the collaboration strategy to track the fire front and conduct suppression efforts simultaneously.

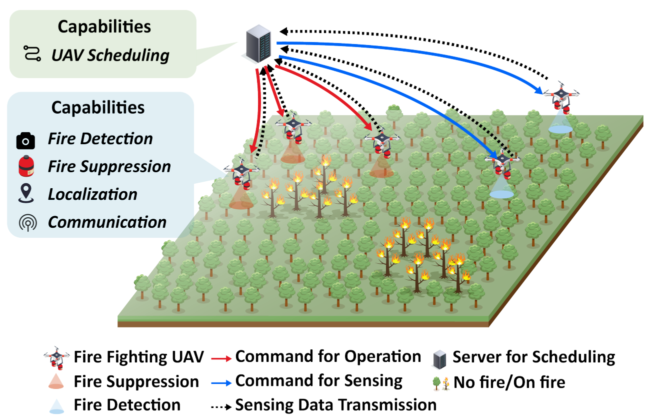

Fig. 1. Illustration of scheduling multi-UAV for wildfire suppression. The server integrates data from all UAVs and sends scheduling commands to UAVs for fire monitoring and suppression simultaneously.

II. System Model

FireHunter is a collaborative multi-UAV scheduling framework that aims at proactive and adaptive suppressing wildfire in a timely manner. We detail its three main modules as follows:

Collaborative Perception & Prediction Model. This component takes the measurement of the environment from multiple collaborative UAVs as input, and then leverages Bayes Filter to fuse sensing data and estimate the environment state. This module also allows a prediction step to support the nonmyopic planning of UAVs.

Spatio-temporal Confidence-aware Assessment Model. This component is the core of *FireHunter*, which introduces a novel utility function to assess the utility of locations based on the predicted environment state. It begins by estimating the

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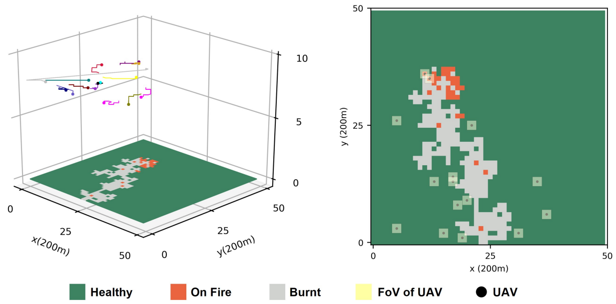


Fig. 2. An example snapshot of the simulation experiment. *Left:* 3-dimensional view. Dots and lines in various colors denote distinct UAVs and their trajectories, respectively. *Right:* 2-dimensional view. Translucent rectangles around the UAVs indicate their field of view (FoV).

sensing gain and operation gain for each location using the predicted environment state. Next, it constructs a confidence map to integrate the sensing gain and operation gain measures into a unified utility function.

Priority Graph-instructed Scalable Scheduler. This component first constructs a priority graph based on the utility assessment results to facilitate the path search. Next, it provides a sequential allocation scheme to generate collaborative paths for multiple UAVs, which efficiently reduces the computation complexity from exponential to linear.

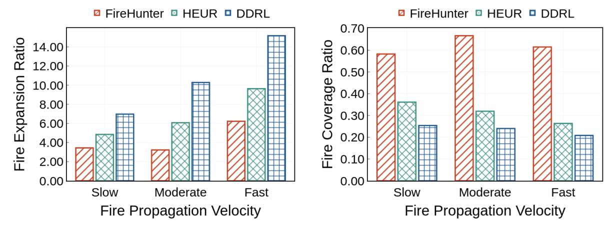
III. Evaluation

Implementation and Methodology. To validate the performance of *FireHunter* under various environmental conditions in a large-scale terrain with more UAVs, we conduct evaluations with respect to the most significant environmental factors [6]: fire propagation velocity. To mimic real-world wildfire fighting scenarios with UAVs, we simulated a terrain of $10km \times 10km$ and discretized it into 50×50 cells, as shown in Fig. 2. The default number of UAVs is set as 15.

Evaluation Metrics. • Fire expansion ratio (FER): It evaluates the operation performance by measuring the average ratio of increase in fire and burnt out area after the mission to the initial fire area. • Fire coverage ratio (FCR): It evaluates the sensing performance by measuring the average fraction of ground truth fires covered by the UAVs over the full mission period.

Experiment Results. Fig. 3(a) measures the average FER for all scenarios after experiments, comparing with two baselines. The results show that *FireHunter* outperforms HEUR and DDRL under all scenarios. The FER increases with the growth of fire propagation velocity, which indicates an increasing difficulty in timely fire suppression. As for the performance in the most challenging fast-evolving scenario, the FER of *FireHunter* is 6.22, which outperforms DDRL by 59.1% and exceeds HEUR by more than 35.4%.

We also evaluate the average FCR as shown in Fig. 3(b). With the increase of the fire propagation velocity, the FCR of two baseline methods decrease. In contrast, our *FireHunter* remains an FCR of more than 0.55 under all fire velocities, outperforming baselines. This is because *FireHunter* actively



(a) FER comparison (b) FCR comparison

Fig. 3. **Overall performance of *FireHunter* and baseline methods.** (a) Impact of fire propagation velocity on FER. (b) Impact of fire propagation velocity on FCR.

evaluates the information gain throughout the mission, enabling the UAVs to revisit the uncertain areas and thus discover more regions that just transited from healthy into burning.

IV. Conclusion

This paper proposes *FireHunter*, a multi-UAV scheduling framework that collaboratively estimates and predicts the environment, identifies optimal locations, and plans trajectories non-myopically. Extensive experiments prove its superior performance, showcasing its ability to integrate with existing disaster modeling for efficient emergency response.

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