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Automated Task Generation for Multi-Drone Search and Rescue Operations

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Abstract. Drones are currently an indispensable tool for emergency response teams performing wilderness Search And Rescue (SAR), as they can cover large and possibly inaccessible areas efficiently. It is, however, still unclear how a drone operator can effectively engage and control a system composed of multiple autonomous robots, especially in unstructured and outdoor environments. This paper reports on ongoing work in the project HERD — Human-AI Collaboration: Engaging and Controlling Swarms of Robots and Drones [6], in which we focus on how to enable an operator to control multi-drone systems. We present a tool for generating tasks and plans for multiple drones in wilderness SAR scenarios. The central aspect of our approach is to improve the search quality by automatically generating tasks to ensure timely coverage of high-risk areas, such as ditches, lake/sea banks, and beneath tree lines, where distressed people are likely to be found.

Keywords: Multi-Drone Systems · Search-and-Rescue · Decentralized Coordination

1 Introduction

Drones have become a valuable tool for emergency response teams conducting search-and-rescue operations [9]. Drones can effectively cover large and possibly inaccessible areas [13, 6], while capable of solving complex missions effectively [3]. Single-drone systems are typically operated through remote control or have limited autonomous decision-making capabilities. On the other hand, multi-drone systems have a lot of potential since the drones can work in parallel, covering a search area more effectively than a single-drone system. It is, however, still unclear how a drone operator can effectively engage and control a system composed of multiple autonomous robots, especially in unstructured and outdoor environments. This paper reports on ongoing Ph.D. research in the project HERD — Human-AI Collaboration: Engaging and Controlling Swarms of Robots and Drones [6], in which we focus on how to enable an operator to control multi-drone systems. However, to effectively conduct a search using a multi-drone system, it needs to be controllable by a single operator, which means that the system must have a relatively high level of autonomy. For example, it should be able to automatically assign search trajectories to drones based on a high-level mission specification [9, 8]. Multiple solutions to the task allocation problem, both centralized and decentralized, have been presented [2, 15, 4, 8], as well as extensions to accommodate for convergence time [14] and complex tasks [8]. However, it is still unclear (i) how to automatically generate realistic SAR tasks, and (ii) how to prioritize the tasks to conduct a SAR mission most efficiently. It is important to model the priorities of the drones appropriately to ensure that urgent tasks are addressed first. Additionally, any changes in the priorities need to be effectively communicated to the drone(s), to convey the intent of the operator. This is vital to ensure the rescue team can respond quickly and efficiently to changing situations. Especially when potential targets are located, the next steps need to be planned carefully. In my Ph.D., we aim to find answers to these questions regarding autonomous search-and-rescue operations.

2 Problem Statement

In multi-drone systems for search and rescue, the problem of multi-task assignment arises frequently [13]. One such use case is in SAR missions, where multiple drones need to be assigned different tasks, such as reconnaissance or area coverage. To solve this problem, a decentralized algorithm, called the *consensus-based bundle algorithm* (CBBA) [4], has been proposed. CBBA is an auction-based algorithm that can be used to solve the *multi-drone multi-task* assignment problem. The algorithm iterates between a bundle-construction phase, in which tasks are assembled into bundles based on their availability and priority, and a conflict-resolution phase, in which consensus is reached on the allocation of tasks to drones. The task-allocation algorithm aims to assign a list of N_a drones to N_t tasks without any conflicts while maximizing a global objective. In a mission, the global objective function is the sum of all local objective functions for each drone. The local reward is based on the tasks assigned to the drone and the order of their execution. The underlying problem of CBBA, the *multi-drone and multi-task assignment* problem, can also be formulated as a mixed-integer linear programming (MILP) problem [10]:

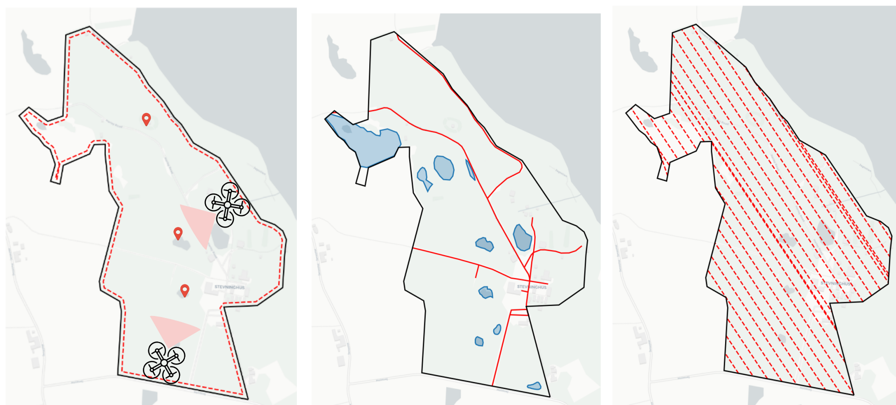
$$\begin{aligned} &\max_{\mathbf{x},\boldsymbol{\tau}} \sum_{i=1}^{N_\mathrm{a}} \sum_{j=1}^{N_t} F_{ij}(\mathbf{x},\boldsymbol{\tau}) x_{ij} \\ &\text{s.t. } \mathbf{H}(\mathbf{x},\boldsymbol{\tau}) \leq \mathbf{d} \\ &\quad\ \mathbf{x} \in \{0,1\}^{N_a \times N_t}, \boldsymbol{\tau} \in \left\{\mathbb{R}^+ \cup \emptyset\right\}^{N_a \times N_t}, \end{aligned} \tag{1}$$

where F_{ij} is the score function for drone i servicing the task j, with respect to the tasks assigned to the drone. $\mathbf{H}$ and $\mathbf{d}$ define a set of N_c possibly non-linear constraints $x \in \{0,1\}^{N_a \times N_\mathrm{t}}$, is a set of $N_a \times N_\mathrm{t}$ binary decision variables, x_{ij}, to indicate the assigned task j to an drone i. $\boldsymbol{\tau}$ is a set of real-positive variables τ_{ij}, describing when drone i will service the task j [10]. In the context of a SAR operation, F_{ij} represents the value for covering a search area, or a part of a search area, for instance following a certain trajectory [8], and the constraints $\mathbf{H}$ represent energy limitations, no-fly zones, and so on. In this Ph.D. project, we have proposed to utilize CBBA [4], to solve the *multi-drone multi-task* assignment problem in equation 1, where each drone creates a greedy assignment of the tasks and creates a consensus with other drones about the allocation. The greedy assignment is made using a trajectory task assignment extension to CBBA, which allows for evaluating tasks modeled as trajectories, such as coverage tasks [8]. Additionally, using *bid warping* [10] allows for more complex objectives. However, whenever a complex mission is changed dynamically, it becomes necessary to develop strategies for efficient reallocation of resources.

3 OFS: The Overview, Focused, Systematic search method

In this Ph.D., the main focus is cooperation between autonomous drones toward solving a common goal while allowing operators to control the overall objective. Therefore, it is important to consider existing frameworks and domain experience. The *Danish Emergency Management Agency* (DEMA) has developed a framework called: *Overview*, *Focus*, *Systematic* (OFS), for conducting SAR operations using drones, including prioritization of tasks in different environments. Our approach utilizes the OFS-method as the foundational reasoning tool, to ensure that the operator can conduct a mission efficiently using our multi-drone approach. By utilizing the OFS-method we can model tasks and facilitate dynamic re-planning strategies, making SAR operations more efficient. The OFS-method has been developed based on multiple international best practice reports and guides to manual search and rescue in two internal field trials conducted by DEMA, where their best practice methods were compared to the OFS-method [1]. DEMA has conducted extensive research on drones for emergency management, including interviews with key personnel and workshops with national emergency management agency divisions. They used various sources such as IEDO best practice report [1], EENA drone efficacy study [7], and Lost Person Behavior application which is based on the International Search and Rescue Incident Database (ISRID) [11], with over 50.000 incidents. Based on this research, DEMA conducted four field trials comprising 18 experiments and 180 simulated missing persons. The OFS search method has three phases: *Overview*, *Focused*, and *Systematic*. Before starting, it is important to know about the missing person's mental state, behavior, and last known location. The *overview* phase consists of an overview rotation and an overview route, where a drone covers the search area and creates markers used in the next phase based on the missing person's behavioral profile. An overview route is illustrated in Fig. 1a.

The *focused* search consists of a *high-risk-search* and a *probabilistic-search*, where both types are identified in the *overview* phase. The *high-risk-search* has the highest priority, as the person's health might be at risk, and, therefore, it is



(a) (b) (c)

Fig. 1: (a) Shows a search in an urban area with a *overview* route marked with the dashed red line, including targets of value illustrated by the red map markers. (b) Illustrates the tasks in the *focused* phase, where roads and wetlands are marked with red and blue respectively. (c) The coverage pattern is illustrated as red dashed lines and is used in the *systematic* phase.

important to cover. The *probabilistic-search* consists of places where the person is most likely to end up and is based on statistics from the ISRID dataset, and is illustrated in Fig. 1b. The *systematic* phase consists of a search using a set of boustrophedon coverage patterns [5] with a specific flight configuration, consisting of an altitude, camera angle, and speed, that enables a drone operator assistant to analyze the camera feed in real-time and is shown in Fig. 1c. In some scenarios, a second coverage is performed, but perpendicular to the previous search, which increases the probability of detection.

4 Translating OFS into Multi-Drone Objectives and Tasks

In search-and-rescue operations, drone operators often face a wide range of environments in which the type of coverage tasks vary widely. These tasks are usually created manually and require careful consideration of various environmental factors and seasonal changes. However, to improve efficiency and accuracy, we are exploring automated approaches to task generation. We utilize data from OpenStreetMap [12] and local weather information, we propose a system that automatically generates tasks for drones based on the current environment. Our previous work [8] generalized the notion of *tasks* to include trajectories, taking into account the spatial nature of coverage planning in the decentralized market-based task allocation algorithm CBBA, which will be utilized in the task generation. In the OFS-method, DEMA identifies potential pitfalls in conducting a search-and-rescue operation in different environments. To determine high-probability areas, modeling the individual's profile is crucial. Our tool, *TrajGenPy* [3], automates the task generation based on environmental features while taking into account the OFS-method. Flat terrain may appear easy to navigate using drones, but assuming complete coverage can be dangerous as environmental features such as gorges, ditches, and vegetation may obstruct the view. Hilly terrain presents a challenge in discovering targets because of the landscape, often covered by forests or foliage, which complicates target identification. In areas containing wetlands, careful consideration must be given to wind and water currents because waves can create blind spots, which impact the effectiveness of the systematic search patterns. Urban searches are complex due to the number of locations where a person might seek shelter. During emergency response missions, teams have to adapt to changes in information and adjust their priorities accordingly. This means that operators need to be able to engage with a multi-drone system and make changes on the fly. In the event of a potential survivor being detected or a change in mission priorities, drones may need to apply different strategies based on their circumstances. For instance, withholding information from drones that cannot perform the task in a suitable time frame may be necessary to allow for more efficient use of resources. By not considering drones that are unlikely to accept the task, time and energy can be focused on drones that are more likely to complete it within the desired time frame. We evaluate a drone's ability to perform a certain task based on different criteria, such as the minimum travel time in the environment or a deadheaded travel time to the task. To assess the performance of the re-planning strategies and the objective functions based on the OFS-method, we will define a common performance metric. Commonly, a performance measure of a CBBA system is given as the sum of objective functions for each drone or the amount of allocated tasks [10, 14, 2]. Though this might not be representative of a SAR operation, as the global goal is to find a potential survivor as fast as possible, therefore a more fitting metric is to evaluate the *time to detection* given an environment with targets sampled throughout the environment, based on real incident data, for example from the ISRID database.

5 Discussion and Future work

In this paper, we presented ongoing work on a tool, *TrajGenPy*, for generating tasks for search-and-rescue operations. This tool leverages environmental features and specifications from the OFS-method to generate effective search-and-rescue tasks. Further research will be conducted to test this tool using the same field trials provided by DEMA and sampled data from real SAR incident reports. Additionally, we plan to explore multi-drone search-and-rescue scenarios, prioritizing tasks in a manner similar to the OFS-method. Our ultimate goal is to allow operators to engage with multi-drone systems and improve the efficiency of search-and-rescue operations.

[3] https://github.com/kasperg3/trajgenpy

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