Collective Search in Unknown Dynamic Environments using MAVs

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***Abstract*—This paper provides an architecture for a swarm of autonomous MAVs performing a collective search in an unknown and dynamic environment. The search mechanism is based on a modified version of a classical PSO with collisions avoidance. Additionally each swarm entity uses a real-time multi-criteria decision making algorithm to be able to select from a set of Pareto-optimal actions according to own specified preferences on energy-consumption and search results. This behavior of MAvs provides an enhanced search mechanism for harsh environmental conditions. Additionally, the energy-awareness enables the swarm entities to react to low battery levels by adapting their decisions over the search process.**

I. INTRODUCTION

Unknown dynamics (such as wind) in search environments pose a variety of challenges for autonomous robotic search tasks. In this paper, we focus on a group of small-scale autonomous MAVs (Micro Aerial Vehicles) which are supposed to collectively search for certain goals. Examples of such goals are i.e., specific objects/materials, high concentration of smoke, radioactivity or toxicity. The resulting information is very beneficial for search and rescue scenarios. Using a group of MAVs has several advantages. The first concerns the robustness against failures (failure in one or two does not heavily influence the overall functionality) and secondly, they can simultaneously cover/search a large area in parallel. Moreover, these robots can be used in areas which are too dangerous for human beings, while their maneuverability permits to reach hardly accessible areas. In this paper, we present an architecture to apply a group of MAVs [1] in indoor and outdoor search scenarios with dynamic and unknown environments, where the dynamics of the environment are considered to be airflow produced by the MAVs themselves and the external wind. Such dynamic environments can influence the search and additionally the performance of the individual MAVs. For instance MAVs flying against the flow consume more energy, while those flying alongside the flow benefit from the external forces. The goal of our proposed architecture is to provide a framework for an efficient exchange and exploitation of information in the swarm to enable optimization of energy consumption. We additionally focus on individual decision making algorithms in MAVs.

II. GENERAL MODEL

In our proposed model, we consider a swarm of n MAVs as shown in Figure 1. The architecture considers the swarm of MAVs to be composed of multiple autonomous individual entities that cooperate towards a common goal. The swarm approximates the current environmental situation based on each entitie's sensor readings. This information is composed to form a local representation of the current state of the environment regarding the global environmental model in terms of time and space. This information is shared with local neighbors together with the current behavior. To this end, each MAV is equipped with a communication module to allow wireless transmission of information to neighboring MAVs. We currently do not consider multi-hop communication, as the information propagation is done by the collaborative search mechanism. The local behaviors of each MAV ensure that no invalid actions such as moving into obstacles and getting close to each other are performed. The decision mechanism applied to control the collaborative search uses an energy model within each MAV to enable different trade-offs between both the search and the energy efficiencies.

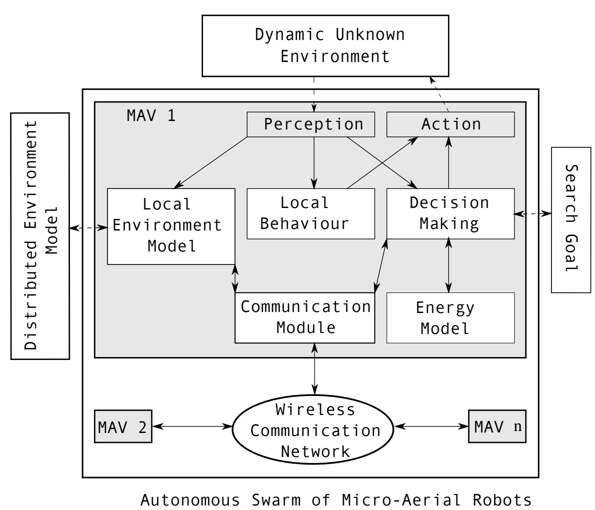

Fig. 1: Architectural Overview of Collective Search using a swarm of MAVs.

III. Dynamic unknown environment

The dynamics of the environment such as wind flows have been extensively studied in the area of fluid dynamics (aerodynamics), vortex methods e.g., [2]. Similarly, we model the dynamics of the environment using vector fields and additionally consider the collective search and information exchange between the MAVs (cf. [3], [4]). In the literature about collective robotic search, dealing with dynamics environment has been studied e.g., in the context of stable outdoor flight formation [5] and swarm of aquatic surface robots [6]. The dynamic environments influence the movement of the MAVs and therefore the corresponding energy consumption. The energy consumption of MAVs is in fact a critical issue for search scenarios. In general, managing the energy resources is a major concept in accomplishing a task by autonomous systems [7]. This is notably evident with MAVs, which have severely limited battery of typically 10 to 15 minutes [8]. [9] recently published a survey paper about both Hardware and algorithmic approaches to improve the efficiency of aerial vehicles. In our architecture the energy model (Fig. 1) provides information about the status of the energy level to the Decision Making module. The Decision Making module additionally considers the information from other MAVs and the local information about the progress of the search, which will lead to an action in form of a movement (next section).

IV. Collective Search and Individual Decision Making

Collective robotic search algorithms in unknown search landscapes typically rely on communication between MAVs which is illustrated by the Wireless Communication Network in Fig. 1. In addition, the information about the search landscape at the current position is gathered by each MAV. Using the communication, the MAVs can exchange their local information about the search landscape (Fig. 1) which can be used to compute a flying direction for certain time steps in the future. Here we use a variation of Particle Swarm Optimization (PSO) with collision avoidance e.g., [3]. PSO has already being used in collective robotic search considering the external unknown environment such as plume detection, i.e. odor source localization problems [10]. In our architecture, we go one step further and include an individual decision making method to select a new moving direction by considering both the current search progress and the dynamics in the environment. These two goals can be in conflict with each other, as one optimal direction in terms of search landscape, might be largely influenced by the external dynamics (opposite wind). Therefore, the MAVs need to run a multi-criteria decision making algorithm to decide about the next moving direction (Fig. 1, Decision Making). In this case each MAV optimizes the following goals to find a set of so called Pareto-optimal directions for the next movement:

- Minimize the energy consumption mainly caused by the dynamics in the environment
- Minimize the search time

The final direction can be selected from the set of Pareto-optimal directions using pre-defined or adaptive preferences. In [11] and [4], we studied an energy-aware search mechanism for a swarm of MAVs. Our results show that the energy efficiency can result from a multi-criteria decision-making process performed by each MAV. That is, the individuals can decide between profit (efficiency in terms of search) and cost (in terms of energy) by selecting appropriate trajectories according to their available energy and the dynamics in the environment. Different from group decision making in swarm robotics [12] which require a large computation time, individual decision making can be efficiently used for time critical and real-time applications as in our architecture.

V. Conclusion

This paper described our novel architecture to use a swarm of autonomous MAVs in collective search. The resulting systems incorporate estimations of the dynamic state of the environment, the available energy of the swarm entities and the current state of the search. This information is used to decide on the actions of each swarm entity. The decision making selects Pareto-optimal actions according to specified preferences. The resulting behavior enhances the trade-offs between robustness, search results and energy consumption. It enables longer missions especially in harsh environmental conditions.

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