Task Coordination and Trajectory Optimization for Multi-Aerial Systems via Signal Temporal Logic: A Wind Turbine Inspection Study

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Abstract— **This paper presents a method for task allocation and trajectory generation in cooperative inspection missions using a fleet of multirotor drones, with a focus on wind turbine inspection. The approach generates safe, feasible flight paths that adhere to time-sensitive constraints and vehicle limitations by formulating an optimization problem based on Signal Temporal Logic (STL) specifications. An event-triggered replanning mechanism addresses unexpected events and delays, while a generalized robustness scoring method incorporates user preferences and minimizes task conflicts. The approach is validated through simulations in MATLAB and Gazebo, as well as field experiments in a mock-up scenario.**

FULL-VERSION

The full-version of this paper is available at `https://arxiv.org/abs/2409.12713`. To reference, see [1].

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are increasingly used for inspecting civilian infrastructure such as pipelines, wind turbine blades, power lines, towers, and bridges. Traditionally, these inspections rely on skilled operators and onboard sensors, but this approach carries safety risks, high costs, and potential human error. Although automated UAV inspection methods have been proposed, they still face challenges related to navigation reliability, battery limitations, radio interference, and unpredictable environmental conditions [2].

This work presents a novel approach using Signal Temporal Logic (STL) for task assignment and trajectory generation in collaborative multi-UAV inspection missions. STL is employed for its capacity to define complex mission objectives and time constraints in a natural language-like format while providing robustness metric to quantify how well these requirements are met. The approach formulates an optimization problem to generate safe, feasible trajectories that maximize robustness under dynamic constraints.

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A wind turbine inspection serves as a case study to validate the method, which involves coordinating multiple UAVs to avoid collisions, manage time-bound tasks, and respect vehicle dynamics while ensuring full coverage of he infrastructure. A two-step hierarchical strategy is used: first, a Mixed-Integer Linear Programming (MILP) model simplifies the initial mission objectives, and then a global STL optimizer refines the trajectories based on the MILP solution. The method also includes an event-triggered replanning mechanism to adjust UAV trajectories in response to unforeseen events and a robustness scoring technique to address user preferences and task conflicts. Its effectiveness is demonstrated through MATLAB and Gazebo simulations and field experiments in a mock-up scenario.

II. PROBLEM DESCRIPTION

This paper focuses on coordinating a fleet of multirotor UAVs for collaborative inspection missions, using wind turbine inspection as a case study. The mission involves capturing videos and images of the turbine's pylon and blades, divided into two tasks: *pylon inspection*, which evaluates the structural integrity of components like the nacelle and rotor shaft to detect hazards such as corrosion or damage, and *blade inspection*, which scans the entire blade surface for cracks or coating damage, requiring precise UAV control for full coverage without blur. The planning process must consider the turbine's size and UAV dynamics, including heterogeneous velocity and acceleration limits, to generate efficient trajectories that maintain safe distances from obstacles and other UAVs. A pre-existing map with a polyhedral representation of obstacles is assumed for mission planning.

III. PROBLEM SOLUTION

Consider a discrete-time dynamical model of a UAV represented as $x_{k+1} = f(x_k, u_k)$, where $x_{k+1}, x_k \in \mathcal{X} \in \mathbb{R}^n$ are the system states, and $u_k \in \mathcal{U} \in \mathbb{R}^m$ is the control input. The time vector $\mathbf{t} = (t_0, \dots, t_N)^\top \in \mathbb{R}^{N+1}$, with N samples and sampling period T_s. The state sequence $\mathbf{x}$ and control input sequence $\mathbf{u}$ for the d-th multirotor UAV are defined as ${}^d\mathbf{x} = ({}^d\mathbf{p}^{(1)}, {}^d\mathbf{v}^{(1)}, {}^d\mathbf{p}^{(2)}, {}^d\mathbf{v}^{(2)}, {}^d\mathbf{p}^{(3)}, {}^d\mathbf{v}^{(3)})^\top$ and ${}^d\mathbf{u} = ({}^d\mathbf{a}^{(1)}, {}^d\mathbf{a}^{(2)}, {}^d\mathbf{a}^{(3)})^\top$, where ${}^d\mathbf{p}^{(j)}$, ${}^d\mathbf{v}^{(j)}$, and ${}^d\mathbf{a}^{(j)}$ represent the UAV's position, velocity, and acceleration sequences along the j-axis of the world frame. The k-th elements of ${}^d\mathbf{p}^{(j)}$, ${}^d\mathbf{v}^{(j)}$, ${}^d\mathbf{a}^{(j)}$, and $\mathbf{t}$ are denoted as ${}^dp_k^{(j)}$,

${}^{d}v_k^{(j)}$, ${}^{d}a_k^{(j)}$, and t_k. The STL grammar (omitted for brevity) is used to encode the inspection problem as:

$$\begin{aligned}\varphi = &\bigwedge_{d\in\mathcal{D}} \square_{[0,T_N]}({}^{d}\varphi_{\mathrm{ws}} \wedge {}^{d}\varphi_{\mathrm{obs}} \wedge {}^{d}\varphi_{\mathrm{dis}}) \wedge \\ &\bigwedge_{q=1}^{N_{\mathrm{tr}}} \lozenge_{[0,T_N-T_{\mathrm{ins}}]} \bigvee_{d\in\mathcal{D}} \square_{[0,T_{\mathrm{ins}}]} {}^{d}\varphi_{\mathrm{tr,q}} \wedge \\ &\bigwedge_{q=1}^{N_{\mathrm{bla}}} \lozenge_{[0,T_N-T_{\mathrm{bla}}]} \bigvee_{d\in\mathcal{D}} \square_{[0,T_{\mathrm{bla}}]} {}^{d}\varphi_{\mathrm{bla,q}} \wedge \\ &\bigwedge_{d\in\mathcal{D}} \lozenge_{[1,T_N]} {}^{d}\varphi_{\mathrm{hm}} \wedge \\ &\bigwedge_{d\in\mathcal{D}} \square_{[1,T_N-1]} \left({}^{d}\varphi_{\mathrm{hm}} \Longrightarrow \bigcirc_{[0,t_k+1]} {}^{d}\varphi_{\mathrm{hm}}\right).\end{aligned} \tag{1}$$

This STL formula φ encodes both safety and task requirements for the collaborative inspection mission of δ UAVs in the set $\mathcal{D}$ over the mission duration T_N. *Safety requirements* include remaining in the workspace (${}^{d}\varphi_{\mathrm{ws}}$), avoiding obstacles (${}^{d}\varphi_{\mathrm{obs}}$), and maintaining safe distances between UAVs (${}^{d}\varphi_{\mathrm{dis}}$). *Task requirements* include pylon inspection (${}^{d}\varphi_{\mathrm{tr}}$), which involves visiting the N_{tr} target areas for at least T_{ins}, and blade inspection (${}^{d}\varphi_{\mathrm{bla}}$), which requires scanning the blade surface at a specific distance and speed for at least T_{bla}, with N_{bla} indicating the blade sides to cover. Each UAV must also return to its initial position (${}^{d}\varphi_{\mathrm{hm}}$). The following equations define these specifications:

$${}^{d}\varphi_{\mathrm{ws}} = \textstyle\bigwedge_{j=1}^{3} {}^{d}\mathbf{p}^{(j)} \in (\underline{p}_{\mathrm{ws}}^{(j)}, \bar{p}_{\mathrm{ws}}^{(j)}), \tag{2a}$$

$${}^{d}\varphi_{\mathrm{obs}} = \textstyle\bigwedge_{j=1}^{3} \bigwedge_{q=1}^{N_{\mathrm{obs}}} {}^{d}\mathbf{p}^{(j)} \notin (\underline{p}_{\mathrm{obs,q}}^{(j)}, \bar{p}_{\mathrm{obs,q}}^{(j)}), \tag{2b}$$

$${}^{d}\varphi_{\mathrm{hm}} = \textstyle\bigwedge_{j=1}^{3} {}^{d}\mathbf{p}^{(j)} \in (\underline{p}_{\mathrm{hm}}^{(j)}, \bar{p}_{\mathrm{hm}}^{(j)}), \tag{2c}$$

$${}^{d}\varphi_{\mathrm{dis}} = \textstyle\bigwedge_{\{d,m\}\in\mathcal{D}, d\neq m} \|{}^{d}\mathbf{p} - {}^{m}\mathbf{p}\| \geq \Gamma_{\mathrm{dis}}, \tag{2d}$$

$${}^{d}\varphi_{\mathrm{tr,q}} = \textstyle\bigwedge_{j=1}^{3} {}^{d}\mathbf{p}^{(j)} \in (\underline{p}_{\mathrm{tr,q}}^{(j)}, \bar{p}_{\mathrm{tr,q}}^{(j)}), \tag{2e}$$

$$\begin{aligned}{}^{d}\varphi_{\mathrm{bla,q}} = &\textstyle\bigwedge_{j=1}^{3} {}^{d}\mathbf{p}^{(j)} \in (\underline{p}_{\mathrm{bla,q}}^{(j)}, \bar{p}_{\mathrm{bla,q}}^{(j)}) \wedge \\ &\mathrm{dist}_{\mathrm{bla,q}}({}^{d}\mathbf{p}) \in (\Gamma_{\mathrm{bla}} - \varepsilon, \Gamma_{\mathrm{bla}} + \varepsilon).\end{aligned} \tag{2f}$$

Here $\underline{p}_{\bullet}^{(j)}$ and $\bar{p}_{\bullet}^{(j)}$ define the rectangular boundaries for the workspace, obstacles, home positions, and target areas. The parameter N_{obs} represent the number of obstacles. Γ_{dis} is the minimum separation between UAVs, and $\mathrm{dist}_{\mathrm{bla}}(\cdot)$ calculates the Euclidean distance between a UAV and the blade surface. The parameters Γ_{bla} and ε represent the minimum required distance from the blade and the maneuverability margin, respectively.

To solve the problem, the robustness $\rho_{\varphi}(\mathbf{x}, t_k)$ is approximated with $\tilde{\rho}_{\varphi}(\mathbf{x}, t_k)$, the following optimization problem is formulated:

$$\begin{aligned}\underset{{}^{d}\mathbf{p}^{(j)},\, {}^{d}\mathbf{v}^{(j)},\, {}^{d}\mathbf{a}^{(j)},\ d\in\mathcal{D}}{\text{maximize}} \quad & \tilde{\rho}_{\varphi}(\mathbf{p}^{(j)}, \mathbf{v}^{(j)}) \\ \text{s.t.} \quad & {}^{d}\underline{v}^{(j)} \leq {}^{d}v_k^{(j)} \leq {}^{d}\bar{v}^{(j)}, \\ & {}^{d}\underline{a}^{(j)} \leq {}^{d}a_k^{(j)} \leq {}^{d}\bar{a}^{(j)}, \\ & \tilde{\rho}_{\varphi}({}^{d}\mathbf{p}^{(j)}, {}^{d}\mathbf{v}^{(j)}) \geq \zeta, \\ & {}^{d}\mathbf{S}^{(j)}, \forall k = \{0, 1, \ldots, N-1\}\end{aligned}, \tag{3}$$

where ${}^{d}\underline{v}^{(j)}$ and ${}^{d}\underline{a}^{(j)}$ represent the lower velocity and acceleration limits, and ${}^{d}\bar{v}^{(j)}$ and ${}^{d}\bar{a}^{(j)}$ denote their upper limits for drone d along each j-axis of the world frame. The minimum robustness threshold $\tilde{\rho}_{\varphi}(\mathbf{p}^{(j)}, \mathbf{v}^{(j)}) \geq \zeta$, provides as a safety buffer to ensure the STL formula φ is satisfied even with disturbances. The shorthand ${}^{d}\mathbf{S}^{(j)}$ represents the motion primitives that follow the drone's dynamics along each axis.

The resulting problem is a nonlinear, non-convex max-min optimization, which is challenging to solve in a reasonable time due to solvers' tendency to converge to local optima. To address this, we compute an initial guess using a simplified MILP formulation based on a subset of the original STL specification φ:

$$\underset{z_{ij|d}}{\text{minimize}} \sum_{\{i,j\}\in\mathcal{V},\, i\neq j,\, d\in\mathcal{D}} w_{ij|d}\, z_{ij|d} \tag{4a}$$

$$\text{s.t.} \sum_{i\in\mathcal{N}_j^{\mathrm{in}}} z_{ij|d} = \sum_{i\in\mathcal{N}_j^{\mathrm{out}}} z_{ji|d},\ \forall j \in \mathcal{T},\ \forall d \in \mathcal{D}, \tag{4b}$$

$$\sum_{d\in\mathcal{D}} \sum_{i\in\mathcal{N}_j^{\mathrm{in}}} z_{ij|d} \geq 1,\ \forall j \in \mathcal{T}, \tag{4c}$$

$$\sum_{j\in\mathcal{N}_{o_d}^{\mathrm{out}}} z_{o_d j|d} = 1,\ \forall d \in \mathcal{D}, \tag{4d}$$

$$\sum_{j\in\mathcal{N}_{o_d}^{\mathrm{in}}} z_{j o_d|d} = 1,\ \forall d \in \mathcal{D}. \tag{4e}$$

The objective function (4a) minimizes the total flight time for the fleet of UAVs, while ensuring that drones do not revisit the same edges unnecessarily. The constraints ensure that UAVs do not accumulate in an area (4b), that all target areas and blade points are visited at least once (4c), and that each UAV starts and returns to its depot (4d) and (4e). Any disconnected subtours in the MILP solution are connected afterwards, as the MILP primarily serves to seed the final STL optimizer. This allows us to save computational time without enforcing complex subtour elimination constraints. $\mathcal{N}_i^{\mathrm{in}}$ denotes the *in-neighborhood*, the set of nodes with an edge entering i, i.e., $\mathcal{N}_i^{\mathrm{in}} = \{j \in \mathcal{V} : (j,i) \in \mathcal{E}\}$. Similarly, *out-neighborhood* is the set of nodes with an entering edge which starts from i, i.e., $\mathcal{N}_i^{\mathrm{out}} = \{j \in \mathcal{V} : (i,j) \in \mathcal{E}\}$.

Due to space constraints, details on the event-triggered replanning mechanism and the generalized robustness scoring method, which dynamically adjust UAV trajectories and resolve conflicts between competing objectives, are omitted. For more information, see [1].

IV. Experimental Results

The effectiveness and validity of the approach are demonstrated through simulations in MATLAB and Gazebo, as well as field experiments carried out in a mock-up scenario. Videos that can be accessed at `https://mrs.fel.cvut.cz/milp-stl`.

References

[1] G. Silano *et al.*, "A Signal Temporal Logic Approach for Task-Based Coordination of Multi-Aerial Systems: a Wind Turbine Inspection Case Study," *arXiv:2409.12713*, 2024.

[2] A. Ollero *et al.*, "Application of Intelligent Aerial Robots to the Inspection and Maintenance of Electrical Power Lines," in *Robotics and Automation Solutions for Inspection and Maintenance in Critical Infrastructures*, K. Loupos, Ed., 2024, ch. 8, pp. 178–201.