Planning to Monitor Wildfires with a Fleet of UAVs

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***Abstract*— We present an approach to plan trajectories for a fleet of fixed-wing UAVs to observe a wildfire evolving over time. Realistic models of the terrain, of the fire propagation process, and of the UAVs are exploited, together with a model of the wind. The approach tailors a generic Variable Neighborhood Search method to these models and associated constraints. Simulation results show ability to plan observation trajectories for a small fleet of UAVs, and to update the plans when new information on the fire are incorporated in the fire model.**

I. Introduction

When wildfires occur, the information on the fire front is key for the responders. Its extent, strength and spreading speed are indeed essential parameters to know in order to define efficient countermeasures. Gathering such information is a difficult task: wildfires may extend over tens of square kilometers, often in remote areas, and their spread is governed by various parameters, among which some are known with large uncertainties – in particular the wind on the ground and the fuel.

Satellite imagery can bring useful information over the whole fire extent [1]. Firefighters can resort to helicopters to gather more timely and precise information such as the flame height, but such operations are costly and risky. A fleet of fixed-wing UAVs equipped with thermal infrared cameras can be more agilely deployed, and can be used to monitor the evolution of wildfires [2], [3].

This article presents an approach to plan wildfire observations for a fleet of UAVs (Fig. 1), in order to provide firefighters with a map of the fire front. This problem raises numerous challenges: the scales of time and distance involved are large, the process to monitor is dynamic, the influence of the wind is predominant for both the UAV and the fire propagation, the UAV motions and observations are constrained, and the various sources of uncertainties impose the revision of the plans after the incorporation of new observations into the fire map.

Approach and contribution: Given initially known characteristics of the terrain, initial observations of the wildfire, *e.g.* as provided by a network of ground fire sensors or satellite imagery, and the wind, a propagation model predicts the fire front for the next hours. These predictions are exploited by a Variable Neighborhood Search (VNS) approach, that plans the trajectories of the UAVs to observe the fire front. Fire observations are integrated into a fire map, which is used to update the observation plans.

The main contribution of the paper is the tailoring of the VNS to cope with realistic models and constraints of the considered application. A generic VNS approach proceeds by evaluating local modifications to a plan, which is a sequence of oriented waypoints, linked by UAV trajectories accounting for kinematic constraints and the wind. Local plan updates include slight modifications of waypoints, and waypoint insertions, which are sampled on the basis of the fire front propagation model. The impact of these plan modifications is evaluated by the predicted fire observations after having updated the UAVs trajectories they entail.

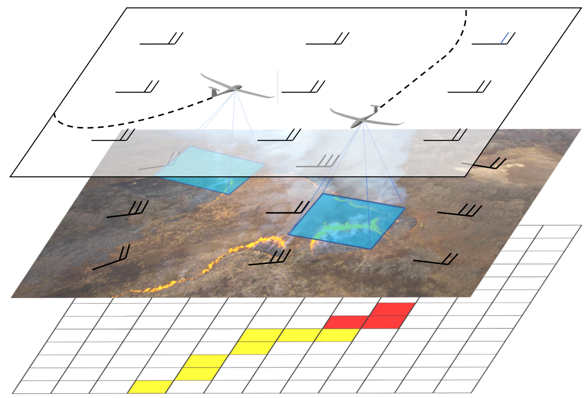

Fig. 1: A fleet of UAVs equipped with thermal cameras fly over a wildfire, at a leveled altitude, where the wind is considered steady and spatially homogeneous. On the ground, the terrain shape generates more complex winds, which govern the spread of the fire front. The lowest layer represents the fire map that incorporates the observations of the UAVs (in red) and the fire propagation predictions (in yellow). This map is meant to be used by the firefighters, but is also the basis upon which further observation trajectories are planned.

Outline: The next section reviews related state of the art, showing that little work has been devoted to *planning* the observations of spreading phenomena. Section III presents the UAV and fire models used in the planning problem formulation. Section IV is the heart of the paper: it depicts how the generic VNS approach is tailored to our specific use-case and associated models. Section V presents results obtained with realistic simulations.

II. Related work

Various research projects have tackled the problem of wildfire remote monitoring. For instance the COMETS European project addressed the use of a heterogeneous fleet of UAVs for cooperative fire detection [4]. The goal

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was to detect, locate and monitor fire spots with aerial vehicles equipped with infrared cameras. More recently, ASAPTERRA focused in automated information processing in the context of hazard response, exploiting in particular satellite imagery for rapid wildfire mapping [1].

The wildfire spread phenomenon is typically described as a front or boundary propagation, and the robotics literature about tracking such phenomena is large. In the case of wildfire monitoring, most approaches are based on distributed boundary tracking, resorting to automatic control solutions. [3] deals with communication constraints of a fleet of UAVs flying along a supposed circular fire front. [5] depicts a wildfire monitoring system using rotary-wing UAVs, focusing both on coverage and tracking. A model-free boundary tracking algorithm have been proposed in [6]. Automatic control approaches are reactive solutions: since wildfires can last up to several days, it is also necessary to *plan* solutions that drive the monitoring resources over the long term.

The observation problem we consider resembles the *Orienteering Problem* (OP) [7]. The solution of the OP is a path visiting vertices of a graph, such that the duration of the path is less than some time budget and a collected score is maximized. There are however some essential differences for the case of wildfire monitoring. First, every location traversed by the fire is a vertex that can be visited: even when the area of interest is discrete, the number of locations is huge, and so are all the possible trajectory combinations. Also, the utility function is not a linear combination of individual rewards, because the value of observing one particular location is time-dependent and highly correlated with nearby observations. While many extensions to the OP and associated solvers have been devised (as surveyed in [8]), none consistently handle all requirements for wildfire monitoring. In addition, fixed-wing UAVs are subject to complex non-linear motion equations due to aerodynamics, atmospheric conditions and actuator performance bounds ([9] tackles the OP with such constraints).

III. Models

A. Fixed-wing UAV motion

We consider a UAV v flying on a horizontal plane (x, y), at some constant altitude z, in which there is constant horizontal wind field (V_{wx}, V_{wy}). The UAV flies at a constant airspeed V_a, and its heading ψ is controlled with a bounded turning rate $|u| \leq \dot{\psi}_{max}$. The kinematic model of the UAV is:

$$\dot{x} = V_a cos(\psi) + V_{wx} \quad \dot{y} = V_a sin(\psi) + V_{wy} \quad \dot{\psi} = u$$

In the absence of wind, the shortest path between two oriented points for such a vehicle is given by Dubins trajectories, composed of maximum curvature sections (arcs of circle) and straight segments [10]. However, this result does not apply when the vehicle is subject to wind. An iterative optimal motion planning algorithm that accounts for a constant wind is proposed in [11]. To compensate the wind-induced drift, the problem is reformulated as follows:

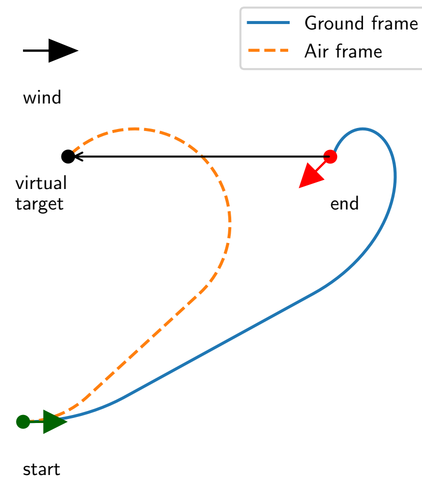

Fig. 2: Dubins trajectory under the presence of constant wind. The UAV is commanded to perform the dashed trajectory to reach the virtual target. Because of the effect of the wind, the real trajectory will be the solid line and hence attain the desired end point.

a ground frame, subject to wind, and an air frame, wind-independent, are introduced. The fixed end point in the ground frame then becomes a moving virtual target in the air frame, with a velocity equal to the wind speed in the opposite direction. The goal of the reformulated problem is to find a Dubins path that reaches the moving virtual target (Fig. 2). This path results in the optimal trajectory to the original target in the ground frame. We use this result to find the shortest path between two oriented points during the planning phase.

B. Wildfire propagation

A wildfire starts from one or more ignition points and then spreads through the surrounding terrain. The direction and speed of spread depend on numerous factors linked to the physics of the fire, the vegetation (fuel), the terrain shape and the wind at the terrain level. Wildfire propagation is a too complex phenomenon to be modeled in exact terms based on thermodynamic and combustion laws. Instead, scientists have defined empirical models, that relate the fire propagation speed and direction to the terrain, fuel and wind. A very common propagation model is the Rothermel model [12], used in most of the support software tools for firefighters.

The Rothermel model exploits information about terrain slope, fuel parameters, and wind speed and direction. Terrain slope is static and known, fuel parameters are defined by the vegetation type and humidity, and can be considered static [13]. The wind at the terrain level is estimated on the basis of a steady wind at a given altitude using WindNinja[1] that exploits the models presented in [14] and the digital elevation map of the terrain.

Our wildfire propagation simulation relies on building a propagation graph over a discrete environment, as proposed

[1] http://firelab.github.io/windninja/

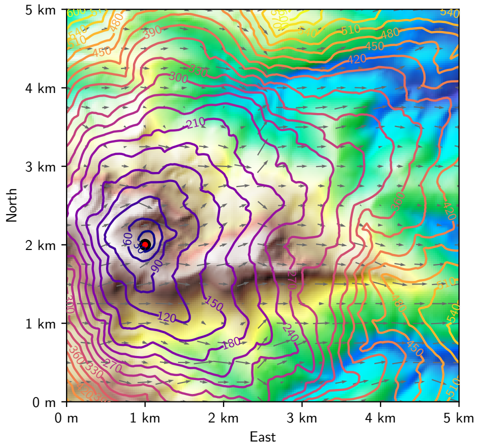

Fig. 3: Result of a fire propagation in a mountainous area. The background color indicates the heights of the digital terrain map, level curves indicate ignition times labeled in minutes relatively to the fire start, denoted as a red dot. Arrows represent the local wind speed and direction. The time required to compute this propagation is about 11s on an Intel Core i7 PC running at 2.70GHz.

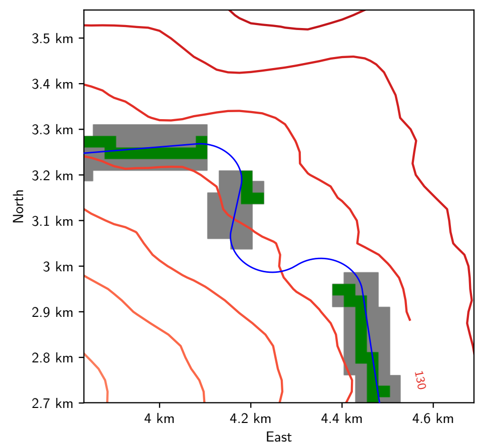

Fig. 4: Observations provided when the UAV is following the trajectory in blue over a fire propagation model. Green patches are the cells that have been observed while on fire, the gray patches are the other observed cells. Observations are only made when the UAV is flying along straight lines.

by [15]. The fire map is modeled by a 25m resolution Cartesian grid, matching the digital elevation map resolution. The shape of the fire front depends on the main propagation direction and the rate of spread from one cell to another [16], both computed using Rothermel's method.

Propagation is initialized by setting the ignition time of one or multiple cells. A cell ignition time is computed as: $\textit{ignition}(x, y) = \min_{(x_n,y_n)\in N_{(x,y)}}\{\textit{ignition}(x_n, y_n) + \textit{travel-time}((x_n, y_n), (x, y))\}$ where $N_{(x,y)}$ are the neighbor cells of (x, y). This process can be seen as constructing a propagation graph, built using Dijkstra's shortest path algorithm.

Once all the neighbor cells are set on fire, the fire front moves away from the current cell. As a simplification, we consider that a cell ceases to be on fire when the fire front moves forward: $\textit{ignition}_{end}(x, y) = \max_{(x_n,y_n)\in N_{(x,y)}}\{\textit{ignition}(x_n, y_n)\}$. This implies that fire at cell (x, y) is observable in the time range $[\textit{ignition}, \textit{ignition}_{end}]$. In other terms, for any given time t there is a set of cells forming a level curve (isochrone) of the fire propagation manifold (Fig. 3).

C. Fire observation model

UAVs are equipped with a downward looking thermal infrared camera used to gather geo-tagged images of the fire. Using a mapping algorithm, the pixels of an image labeled as on fire can be projected to a digital elevation map to create an observed fire map. As for most UAV mapping processes, only images acquired when the camera is pointing close to the nadir are processed: the size of the area seen by the camera depends on the field of view, the UAV position, and the angle at which the camera is pointing. Fig. 4 shows an example of the observations provided by a flight over a simulated fire propagation, in which the camera footprint at nadir is 100×75m (4×3 grid cells).

The ignition time range depicted in Section III-B defines a time slack for the UAV to observe a cell on fire. Incidentally, the level curve geometry of the fire front combined with the size of the camera footprint makes the observation model robust with respect to errors in the trajectory tracking.

IV. Planning observations

Our approach to plan the wildfire observations builds on the VNS metaheuristic that has been applied to numerous combinatorial optimization problems in Operations Research [18]. VNS algorithms are built on a sequence of neighborhoods, where each neighborhood defines a local modification to the plan allowing the generation of closely related plans (neighbors). A simple neighborhood is for instance the swap of two sequenced places to visit.

The principle of VNS algorithms is to repeatedly apply:

1) A descent phase that exploits all neighborhoods to find and apply local improvements to the current plan until no improvement is found.
2) A perturbation phase aiming at escaping local optimums reached during the descent phase.

In our case, we define the plan as a sequence of waypoints to reach for each UAV. The fire observations are derived by an analysis of the Dubins trajectories that link consecutive waypoints.

One of the key benefits of VNS is its genericity and adaptable definition. In particular, the observation plans are iteratively built by the VNS process for the whole set of UAVs: the problem of allocating UAVs to areas to observe is implicitly solved, and does not require any specific process. Also, as a VNS algorithm works by applying small incremental improvements to a plan, it can be stopped at any time or restarted from an existing plan.

The challenge of a VNS approach to solve a given problem resides in its formulation and in the definition of a good set of neighborhoods for solving it in reasonable time. This section depicts the way the VNS is tailored to our problem[2].

A. Problem formulation

Definition 1 (Waypoint): A waypoint w is an intermediate point of the trajectory that a UAV has to reach. A waypoint is represented by a tuple (x, y, ψ) where x, y, correspond to East/North coordinates with respect to a reference frame[3], and ψ is the course angle.

Definition 2 (Trajectory): A trajectory T is defined as a tuple (v, t_0, W) where v is a UAV model as depicted in Section III-A, t_0 is the start time and $W = \langle w_0, \ldots, w_n \rangle$ an ordered sequence of waypoints.

Considering the motion constraints of v and the given t_0, every waypoint w in the trajectory has an associated time $t(w)$. This is calculated by accumulating the travel time between waypoints with Dubins paths. The start, w_0, and end, w_n, waypoints of a trajectory are located at the same position to denote a round trip.

Definition 3 (Flight Window): A *flight window* (v, T, d_{max}, $[t_{min}, t_{max}]$) represents the opportunity for the UAV v to make a trajectory T and whose duration is at most d_{max}. The trajectory should start and end within the time window $[t_{min}, t_{max}]$.

Definition 4 (Plan): Given a set of flight windows $\{F_0, \ldots, F_m\}$, A plan π is a set of trajectories $T = \{T_0, \ldots T_m\}$, in which each trajectory T_i fits within the flight window F_i.

Given C the set of cells ignited during the flight windows of π, our objective is to maximize the total information gathered over all cells in C. We denote $utility(\pi)$ as $\sum_{c \in C} 1/\min_{o \in \pi} dist(c, o)$. The utility brought by an observed cell, o, depends on observations already in the plan: if there is already a nearby observation in the plan, its utility will be low. This formulation captures the important spatial correlation of ignition times in the context of wildfire monitoring.

A plan π is valid only if for every T_i and F_i the following conditions are respected:

- $\langle w_0, \ldots, w_n \rangle$ is a feasible ordered sequence of waypoints for v, meaning that each pair of consecutive waypoints is connected by a valid Dubins trajectory.
- The trajectory is fully contained in the allowed temporal interval, i.e., $t_{min} \leq t_0 \leq t_n \leq t_{max}$ where t_n is the arrival time at w_n.
- The trajectory does not exceed the maximum duration, i.e., $t_n - t_0 \leq d_{max}$.
- The trajectory starts and ends at the UAV base, i.e., $w_0 = w_n$.

[2]A more detailed description, reasoning and statistical analysis of the approach can be found in [19]

[3]The flight altitude z being kept constant at any time, we omit it on the waypoint definition

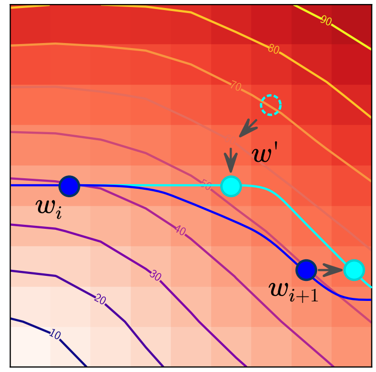

Fig. 5: Waypoint insertion process. A random chosen waypoint w' (dashed, light blue) is inserted in a trajectory between w_i and w_{i+1} (dark blue). w' is re-projected into a previous isochrone (light blue) whose time corresponds to the time needed to reach it from w_i. Finally, due to the increment in travel time between w_i and w_{i+1}, w_{i+1} is moved to a later isochrone.

B. Variable Neighborhood Search

Definition 5 (Neighborhood): A neighborhood $\mathcal{N}$ defines for each valid plan π a set of neighbor plans $\mathcal{N}(\pi) \subseteq \Pi$, where Π is the set of all valid plans.

1) Neighborhoods: We define two types of neighborhoods that have empirically proved useful for our wildfire observation problem.

a) Local Path Optimization: A *local path optimization* neighborhood applies a random or deterministic rotation to a single waypoint in the plan with the objective of reducing the duration of a trajectory.

b) Waypoint Insertion: A *waypoint insertion* neighborhood alters a plan by inserting a new waypoint w' in a trajectory. The quality of a neighbor plan is assessed by the plan utility function, with ties broken by trajectory duration.

In order to focus the search to trajectories close to the fire front, we use an iterative process *projectff* ("project on fire front") that exploits the fire propagation graph depicted in Section III-B. Given a waypoint w_i of a trajectory and a waypoint w to project, *projectff*(w_i, w) returns a waypoint w' such that $t(w') \in [ignition^{w'}, ignition^{w'}_{end}]$, that is, a waypoint w' which is on the fire front when arriving from w_i.

Given a random waypoint w and a trajectory T with waypoints $\langle w_0, \ldots, w_n \rangle$, we construct a neighbor for each $i \in [0, n-1]$ by *(i)* inserting the w' from *projectff*(w_i, w); and *(ii)* for each $j \in [i, n-2]$, replacing w_{j+1} by *projectff*(w_j, w_{j+1}). In a nutshell, this inserts a new waypoint in the trajectory and then updates all subsequent waypoints to make sure they are still on the fire front. This procedure is illustrated in Fig. 5.

2) Shuffling: Typical VNS implementations include some neighborhoods that remove, replace or exchange waypoints between two trajectories. However, we found those to be inefficient in our setting, due to the mostly continuous trajectories in which a waypoint is best considered together with the preceding and following one. Instead, we do shuffling to provide similar benefits at a larger scale.

Definition 6 (Shuffling): A *shuffling function* $f(\pi, k) : \Pi \times \mathbb{N} \rightarrow \Pi$ produces a new plan by introducing a perturbation into the plan π. This perturbation is dependent on the current iteration k of the search.

The shuffling function used here removes a random fraction of each trajectory in the current plan, with the objective of escaping local extrema.

3) VNS Algorithm: The VNS algorithm takes as inputs a sequence of neighborhoods, a shuffling function, a maximum run time, and an initial plan.

The initial plan π_{init} is built by taking an empty trajectory $(v, t_{min}, \langle w_0, w_n = w_0 \rangle)$ for each flight window. It is easy to see that such a plan is valid as the start time and the round trip conditions are respected.

Given π_{init}, the descent phase of VNS tries to generate plan improvements by systematically and sequentially trying all neighborhoods $[\mathcal{N}_1, \ldots, \mathcal{N}_n]$ until a neighborhood $\mathcal{N}_i$ provides an improvement. Particular neighbor plans of $\mathcal{N}_i$ are computed by the *gen-neighbor* function.

Definition 7 (gen-neighbor): Given a plan π and a neighborhood $\mathcal{N}$, the function $\textit{gen-neighbor}_{\mathcal{N}}(\pi)$ returns either (i) a valid plan $\pi' \in \mathcal{N}(\pi)$ such that $utility_{\mathcal{N}}(\pi') > utility_{\mathcal{N}}(\pi)$, or (ii) nil if the neighborhood failed to generate an improving neighbor.

When the neighbor plan computed by *gen-neighbor* gives an improvement, the current plan is updated and the process restarts from the first neighborhood $\mathcal{N}_1$. When *gen-neighbor* is not able to generate an improvement for any $\mathcal{N}_i$, the best plan found so far is perturbed by the shuffling function and the descent phase restarts from the first $\mathcal{N}_1$. This process is repeated until a maximum *runtime* is reached, at which point the best plan found is returned.

V. RESULTS

A. Initial plan

We consider a mountainous region of 5km×5km where multiple fire ignitions occur. We let the algorithm run for 1 minute on an Intel Core i7 PC at 2.70GHz. Fig. 6 shows a scenario with two fire fronts spreading north (the elevation map is only used to compute the fire propagation, and is not shown). Two UAVs starting at different positions are available to observe both wildfires, with a flight duration limited to 10 minutes. The trajectories given by the VNS algorithm follow the fire front to maximize the utility of the plan.

Fig. 7 shows three wildfires being observed by two UAVs taking off from the same base with larger allowed flight duration. The planning algorithm does task distribution implicitly in such a way that the UAVs do not observe the same locations concurrently. Even though they start at the same time, the different paths are planned such that both UAVs arrive at each fire at different times.

B. Replanning

Due to model uncertainty and changing environmental conditions, the actual fire may diverge from the predicted

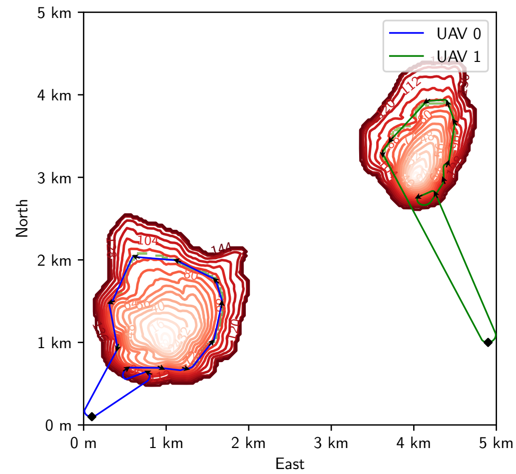

Fig. 6: Plan for a fleet of two UAVs observing two independently spreading wildfires.

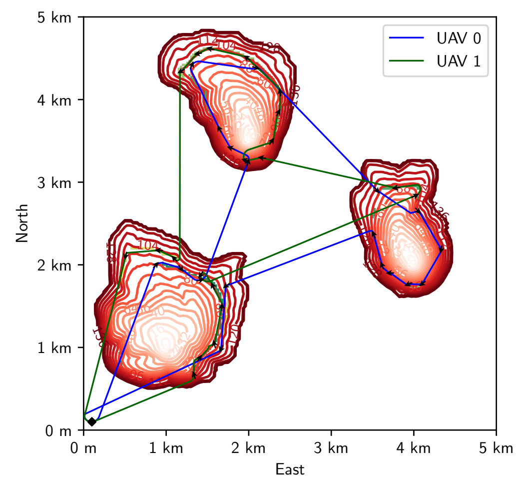

Fig. 7: Plan for a fleet of two UAVs observing three concomitant wildfires.

one. Researchers from the wildfire community recently developed data assimilation approaches that integrate real-time fire front information into the propagation models [20], which in turn allows correcting and improving the parameters that govern the predicted wildfire. We suppose that the observations made by the UAVs can be used by such data assimilation techniques to provide an updated fire map. The monitoring plan should be revised to react to this new situation.

The VNS approach is able to start from any valid plan. In a replanning stage, we use as π_{init} the previously computed plan π_{prev}, and the VNS algorithm is constrained to improve only future parts of it. First, *projectff* translates the future waypoints to ignited locations (waypoints that can not be translated are removed from the plan). Then, the current plan is refined following the procedure described in IV-B.3 for initial plans.

A replanning scenario is shown in Fig. 8. First, the planner

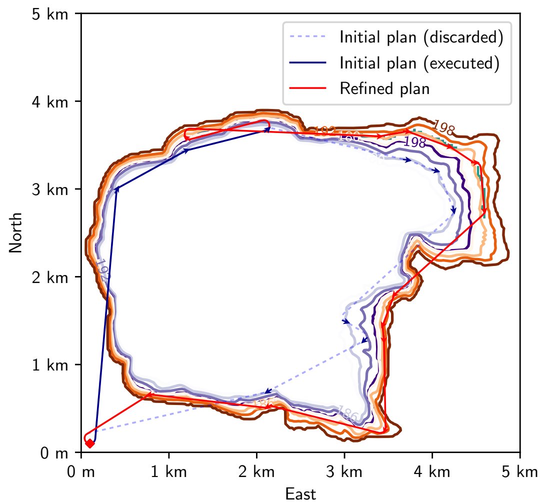

Fig. 8: Replanning scenario. See text for details.

generates the trajectory in blue based on the basis of the predicted fire map in purple. Five minutes later, an update of the predicted fire map is made (e.g. by incorporating data gathered so far by the UAV). This update is shown in orange: the fire actually propagates faster than initially predicted. The planner adapts the remaining of the original plan from minute six, yielding the red trajectory.

VI. Conclusion

We have presented a wildfire monitoring system based on fleets of fixed-wing UAVs: we have modeled the problem by introducing the dynamics of fire propagation and UAV motion in the presence of wind. Then, we have introduced a VNS-based planning algorithm capable of generating plans using this realistic models. Finally, we have shown a small selection of typical wildfire scenarios for which the planning algorithm was able to generate a sound monitoring plan.

In the near future, the monitoring system will be integrated with a real command and control software for UAVs [21], enabling improved UAV simulation and field experiments.

Future work on the algorithmic side will consider exploiting 3D UAV motion, to overcome terrain constraints in mountainous areas and to improve observations. We will also explore approaches that apply an economy of means principle: instead of allowing all the UAVs to exploit their whole flight duration, the number of UAVs to deploy as well as their take-off time should be defined in order to optimize the ratio between resource usage and quality of the observed fire map in the long term. Finally, integrating fire front tracking capabilities to react to discrepancies between the propagation prediction and observations will be considered.

The planning algorithm code and wildfire propagation model are available online at `https://github.com/laas/fire-rs-saop`.

Acknowledgments: This work was partially supported by the European Interreg Sudoe program, through the funding of the FIRE-RS project

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