Autonomous Decisional High-level Planning for UAVs-based Forest-fire Localization

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Abstract: This paper addresses the problem of forest-fire localization using unmanned aerial vehicles (UAVs). Due to the fast deployment of UAVs, it is practical to use them. In forest fires, usually the area to explore is unknown. Thus, existing studies use an automatic or semi-automatic exploration strategy following a zig-zag sweep pattern or expanding spiral search pattern. However, such an approach is not optimal in terms of exploration time since the mission execution and achievement in an unknown environment requires autonomous vehicle decision and control. This paper presents an enhanced approach for the fire localization mission via a decisional strategy considering a probabilistic model that uses the temperature to estimate the distance towards the forest fire. The UAV optimizes its trajectory according to the state of the forest-fire knowledge by using a map to represent its knowledge and updates it at each exploration step. We show in this paper that our planning and control methodology for forest-fire localization is efficient. Simulation results are carried out to evaluate the feasibility of the generated paths by the proposed methodology.

1 INTRODUCTION

Applications of unmanned aerial vehicles (UAVs) have evolved in a dramatic way. The development of the technological aspect has enhanced the operational profile towards assigned tasks. The current operational autonomy is translated into more optimized data collection. The latest ecological trend has also encompassed the inclusion of these aerial agents. Applications such as *weather forecasting*, where the aerial robot performs real-time information gathering of different weather variables, or as animal preservation, where vehicles are able to detect and track hunting-targeted animals, or natural disaster assessment such as floods, hurricanes, forest-fires.

Forest-fires represent a very large issue due to its significant impact, not only environmental or economic but also social. For this reason, efficient localization of forest-fires is a valuable feature during the assessment of this disaster. Dealing with such an event implies a huge mobilisation of resources, either human or material. However, the main problem of forest-fire localization is the lack of time to detect the fire center and to predict its evolution in time. Therefore, well-known capabilities of UAVs, such as their fast deployment, make them a candidate solution for forest-fire localization.

Several works demonstrate that localization of forest-fire is possible (Ambrosia et al., 2003) (Maza et al., 2011). However, existing solutions, UAVs execute predefined tasks that are sequenced and monitored by distant human operators. The communication between the human operator and the UAVs is highly constrained and affect the efficiency of the mission since the human operators are in the control loop.

In this regard, in order to improve the localization efficiency some researchers have embedded *decisional autonomy* that automatically plans or organises the robots activities, controls the execution of their goals and monitors the state of the systems (Di Paola et al., 2015) (Song et al., 2000) (Ingrand et al., 2007). However, these approaches are used in terrestrial and underwater robotics. Other decisional autonomy approaches are implemented in UAVs (Merino et al., 2006). However, the decisional autonomy is related to the low decisional level. High level decisional autonomy is a necessity for autonomous exploration within unknown area.

In this paper, it is embedded a high-level autonomous system adapted for UAVs to explore unknown areas and to detect forest fires sources. In general, exploration strategies deal with limited exploration time and wide forests exploration areas. Since UAVs features limited energy resources is a capital is-

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sue during exploration operations, the paper details an architecture that generates adaptive, cooperative and autonomous decisions for each aerial robot.

Likewise, in order to judge the feasibility of the proposed navigation strategy, a low-level controller is integrated to track the generated paths by the autonomous decisional guidance system.

The outline of the paper is organized as follow. Section 2 presents the previous woks and describe the classical challenges of UAVs associated to a missions achievement. Section 3 details the proposed methodology for autonomous UAVs, UAVs map updates, the exploration strategy and the kynodynamics model. Section 4 shows our architecture implementation used in each UAV. Section 5 presents the effectiveness of our methodology at simulation level.

2 PREVIOUS WORKS AND MISSION CONTEXT

The field of UAVs corresponds to a growing and challenging topic. The application of such UAVs are diverse (Valavanis and Valavanis, 2007) (Chen et al., 2013), they can be used for exploration and data collection, for rescue, fire detection, multi-UAV grasping (Parra-Vega et al., 2012), synchronized flying (Schoellig et al., 2012) and even pole throwing and catching (Brescianini et al., 2013). UAVs can also cooperate to accomplish a common mission (G. Loianno and Kumar, 2015), such as the formation flight (Merino et al., 2010) in which each UAV is keeping a specific distance throw its neighbor, coordinated rendezvous (Beard et al., 2002) to localize fixed targets and avoid threads, coordinated path planning (Nikolos and Brintaki, 2005) and task coordination (Sujit et al., 2005). However, most of the research mainly rely on operational UAV autonomy. This means that UAVs receive a pre-planned tasks without high-level decisional reasoning. A few works intend to introduce the decisional autonomy for UAVs (Merino et al., 2006) such as COMETS (Ollero et al., 2005).This project uses several UAVs, where some of them are directly controlled by an operator and others only rely on their operational autonomy. As a result, these approaches are implemented at low-decisional autonomy level such as perception operations. We consider that decisional task planning has a significant potential to develop novel smart UAVs capable to plan and to organize autonomously while considering distance or time constraints, goals execution and system state verification. In order to provide the aforementioned autonomy, we have developed the proposed architecture using an existing system (T-ReX), which provides an embedded planning and execution control framework (McGann et al., 2007). Finally, a low-level is described considering a rotary-wing configuration UAV. In this sense, a simulation study was carried out regarding the validation of the high-level trajectory planning during the forest-fire localization.

3 METHODOLOGY

This section presents the way information is perceived by UAVs used as a mapping platform in which the probabilities of target presence at a given locations are encoded. Thus, Firstly it is described the forest-fire model. Secondly, we describe the approach to represent the collected data. Thirdly, we explain the proposed exploration strategy for every UAV. Finally, we provided a slight description of the kinematic model of the UAV used to verify the decisional guidance approach.

3.1 Forest-fire Model

Since the goal is the forest-fire detection using different UAVs, let us consider a stationary (slow time-varying) fire model. Considering that the forest fire emission expands proportionally to the altitude, in our model the target is defined according to the maximal known temperature. The density of the temperature T within the forest-fire is a decreasing function of the horizontal distance ρ with respect to the forest-fire center and the elevation z above the ground (Figure 1). This function is the model of the forest on fire,

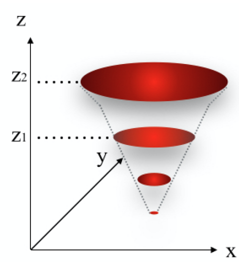

Figure 1: Illustration of the temperature evolution within a forest-fire in stationary weather: the temperature, here represented in red, decreases with the elevation z1, z2 and with the distance to the vertical of the emitting fire.

which is an approximation of the actual diffusion phenomenon: the model is probabilistic and expresses the probability density function (pdf) of the temperature T as a function of the distance ρ and the elevation z:

$$P(T = t|\rho, z) \tag{1}$$

The temperature dispersion is also an increasing function of the distance and the altitude. It is important to notice that in our case several targets can interfere with each other.

3.2 Map Updates

A common representation to map the environment is the occupancy grids (Thrun, 2003). The environment is subdivided into a grid. For each grid square, a probability that the cell contains an obstacle (Moorehead et al., 2001) or a target (Low et al., 2009) is associated. Our choice is to discretize the operational environment and use a grid map of $N \times M$. For each grid $\{x_{i,j}\}$, $i \in [0,N[$, $j \in [0,M[$ cell we associate probability value $P^k(x_{i,j})$. This represents the probability that a fire is located within the cell at time k. Additionally, each cell contains a boolean value initialized to zero. This value is changed to one, if a UAV already visited the cell. This condition allows to avoid fusing twice data acquired from the same position. The cell probabilities are updated incrementally according to a classical Bayesian paradigm under a Markovian assumption as follow:

$$P^k(x_{i,j}) = \frac{P(T^k|x_{i,j} = \text{fire})P^{k-1}(x_{i,j})}{P(T^k)} \qquad (2)$$

where $P(T^k|x_{i,j} = \text{fire})$ is the sensor model and P^{k-1} is the probability value of the fire existence at the time $k-1$. We can observe that the probability $P^k(x_{i,j})$ implicitly represents the precision of the fire-center location. When the probability is equal to 1, means that the fire is perfectly localized.

3.3 Exploration Strategy

The current paper presents the development of a distributed reactive and cooperative exploration strategy based on a probability threshold P_{conf}. The objective of this decisional strategy is to improve the efficiency of the exploration mission, i.e. the detection of forest fire.

In forest-fire detection operations, based on classical approaches, the location of targets are unknown and thus predefined exploration strategies can sometimes be inefficient in terms of time-to-detect or distance covered. In this solution the UAVs can modify their navigation according to their current perception, for this reason such approaches are called reactive approaches. However, most of them do not take into account the collected data during the mission execution (Zhang and Sukhatme., 2008) (Popa et al., 2004).

Thus, in order to counteract the drawbacks associated to reactive approaches the first stage aims at confirming the existence and localization of the closest forest-fire hypothesis, until its probability exceeds a threshold P_{conf}. The UAV heads towards "probable" target while collecting data about the fire hypothesis until its probability exceeds P_{conf}. Doing so, it is reduced the number of vehicle actions, at the cost of less precisely localized center forest fire. Algorithm 1 shows the exploration strategy for each UAV. Four actions are accepted: $a_{left}, a_{right}, a_{front}, a_{behind}$ The UAV choose next cell to explore in order to maximize $P(x_{i,j}/_{x_{i,j}=NE})$. This means that the exploration strategy chooses actions that reaches cells that are not explored and that maximize the expected probability of the target.

$$Max_{a_i \in \{left,right,behind,front\}} P(x_{i,j}/_{x_{i,j}=NE}) \qquad (3)$$

In equation 3, the maximization function is evaluated by one action look ahead. We can generalize the function as follow:

$$Max_{a_i \in \{left,right,behind,front\}} f(z_{\tau(x_i,a_i)}) \qquad (4)$$

Algorithm 1: Next Cell Exploration Algorithm.

Require: D: the diameter of the target ;
$Target_{x,y}$: the coordinate of the target ;
$P(x_{i,j})$: the probability that $x_{i,j}$ is the target;
a: an action ;
τ: transition function.
Update grid using equation (2).
if $(\exists i,j : i \in]0,N], j \in]0,M], P(x_{i,j}) \geq P_{conf})$ **then**
<Target Found>
for $(\forall i,j : i \in]0,N], j \in]0,M])$ **do**
if $(0 < |x_{i,j} - Target_{x,y}| < D)$ **then**
$P(x_{i,j}) \leftarrow 0$;
$P(Target_{x,y}) \leftarrow 1$;
end if
end for
end if
<Choose Next Cell>
$a \leftarrow$ using the equation (3) or (4).
$x'_{i,j} \leftarrow \tau(a, x_{i,j})$
return $x'_{i,j}$

where, $f(z_{\tau(x_i,a_i)})$ is a function that predicts the future values in the Map or GRID, when action a_i is chosen.

3.4 Vehicle Model

In this part, we explain the low-level layer that drives the aerial robot while detecting the forest-fire. In this case, for the purpose of clarity, we restrict the motion to the horizontal plane, following a non holonomic-like motion. For this reason, it is more convenient to address vehicle's translational motion from a kinematic perspective, i.e. focusing on motion resulting

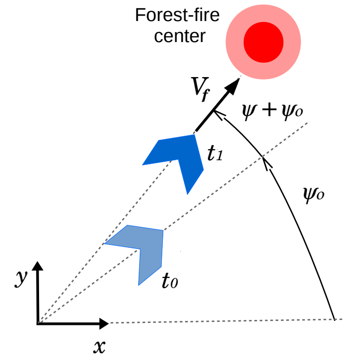

Figure 2: Illustration of a 2D UAV Navigation.

from heading the forward velocity $\mathbf{V}_f$ (see Figure 2), i.e.

$$(\Sigma_\xi) : \vec{\xi} = \mathscr{R}(\psi)\vec{v}_f \rightarrow \begin{cases} \dot{x} & = & v_f \cos\psi \\ \dot{y} & = & v_f \sin\psi \end{cases} \quad (5)$$

whereas the rotational motion within a dynamic framework. The latter configures a 3DOF (three degrees of freedom) *Kynodynamic* model which is expressed by the following equations:

$$(\Sigma_\psi) : \ddot{\psi} = \frac{1}{I_z}\tau_\psi \quad (6)$$

where τ_ψ is the yaw control input.

4 IMPLEMENTATION

The integration of the exploration strategy and the controller for each UAV is implemented using an existing architecture *CoT-ReX* (Cooperative Teleo-Reactive EXecutive) (Belbachir et al., 2012). This architecture is a goal-oriented system, with embedded automated planning and adaptive execution (McGann et al., 2007). Such architecture provides, for each UAV, the capacity to plan, re-plan and execute its mission. Instead of being reactive, this architecture incorporates planners that can cope with different planning horizons[1] and deliberation[2] times. Goals-based mission management *CoT-ReX* allows at the same time being reactive (short planning horizon and deliberation) against new situation such as obstacle avoidance and deliberative such as mission execution. A *CoT-ReX* agent is divided into several layers called reactors. Each reactor can be deliberative or reactive, depending on the horizon and deliberation time. In our implementation, we consider the mission as a maximization problem to locate the forest fire. We assume that the UAV has predefined goals to achieve (e.g. way points) that defines the exploration strategy. To

[1] It is the prediction time.

[2] It is the time that is given to the system to generate a plan.

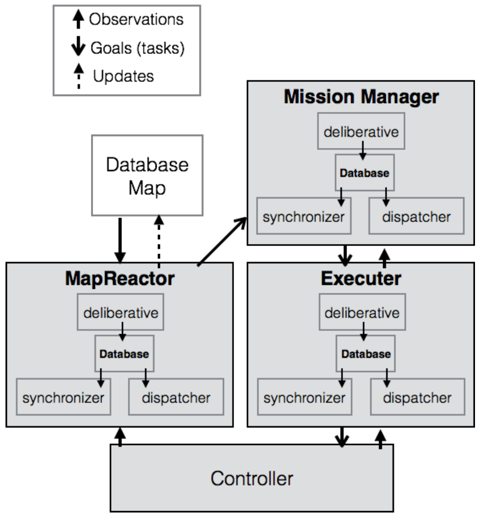

Figure 3: Illustration of the deployed architecture for each UAV.

improve this strategy, the UAV is able to reason on its online perceived data. Additionally, another reactor (*MapReactor*) in the *CoT-ReX* architecture which allows getting up-to-date information on UAV state and modifying its trajectory if necessary. The MapReactor is the component that takes into account the UAV perception generating new goals for the Mission Manager reactor. We assume that the UAV, equipped with the temperature sensors, is able to compute the proximity probability to the forest-fire using equation (1). Figure 3 shows the used architecture. *Mission manager* is responsible of all the exploration area. *Executer* is sending action by action to be executed by the *Controller*. *MapReactor* generates new area to explore.

The low-level layer consider a two-level hierarchical control commonly used for rotorcraft UAVs. Indeed, we have considered a Kynodynamic model that also can be adapted for aircrafts. The controller considers a basic PI control for the translational kinemat-

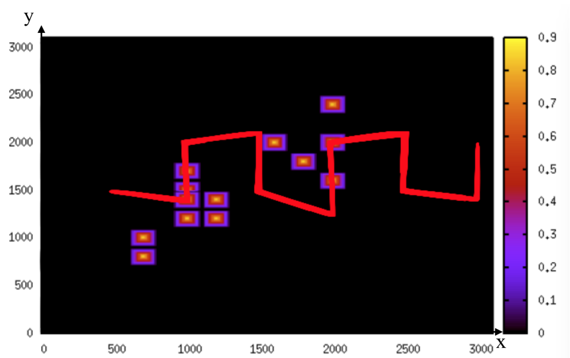

Figure 4: Exemple of an executed UAV trajectory for forest-fire localisation.

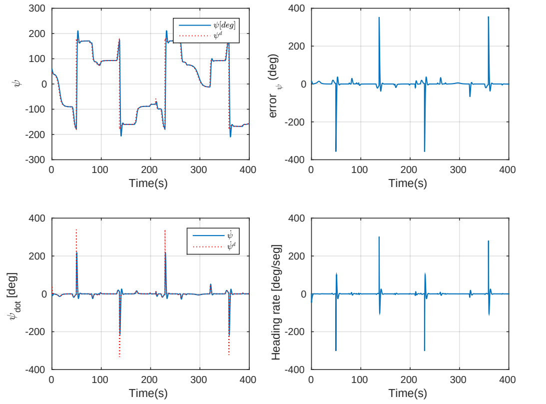

Figure 5: Angular behavior while tracking the 2D trajectory.

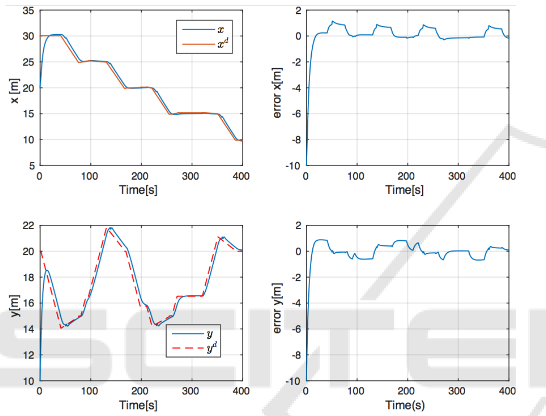

Figure 6: Translational behavior while following the commanded trajectory.

ics defined through stable error polynomials

$$
\begin{aligned}
u_x(e_x) &= -k_{p_x} e_x - k_{i_x} \int_0^t e_x d\tau \\
u_y(e_y) &= -k_{p_y} e_y - k_{i_y} \int_0^t e_y d\tau
\end{aligned}
\tag{7}
$$

where $e_x = x - x^d$ and $e_y = y - y^d$ denotes the error variables, and k_{p_*} and k_{i_*} stands for the stiffness and damping control gains. For the rotational dynamics, a PID control is used to deal with heading of the flying robot.

$$
u_\psi = -k_{p_\psi} e_\psi - k_{d_\psi} \dot{e}_\psi - k_{i_\psi} \int_0^t e_\psi d\tau \tag{8}
$$

where k_p and k_{v_ψ} are positive constants. The control objective is reached introducing the velocity

$$
T = \left[u_x^2 + (u_y)^2\right]^{\frac{1}{2}} \tag{9}
$$

and tracking the desired heading

$$
\psi^d = \arctan\left(\frac{r_2}{r_1}\right) \tag{10}
$$

Table 1: Statistical Results For target localization based on simulation results.

Amount of UAVs	Amount of targets	Explor. time(ut)	Found Targets	%of found targets	Same depth
1	10	100	3	30%	-
1	13	100	4	30%	-
1	20	100	7	35%	-
2	10	100	7	70%	Yes
2	10	100	7	70%	No
2	20	100	13	65%	Yes
2	20	100	13	65%	No
2	30	100	21	70%	Yes
2	30	100	21	70%	No

5 SIMULATION RESULTS

We setup one UAV to explore an area with several forest-fire. A predefined plan is embedded in the UAV. According to the UAV perception, it modifies its plan using its constructed map.

Figure 4 is an example of an executed UAV trajectory, using the developed exploration strategy discussed in section 3.3. Figure 4 represents an horizontal view of the forest-fire. We can see that thirteen forest-fire exists in this example. However, even if the UAV modifies its trajectory it detects four targets. First part of Table 1, represents a statistical experiment with different environment using one and several UAVs. We used different exploration depths for UAVs to evaluate the decisional and cooperative exploration strategy. Each UAV communicates and

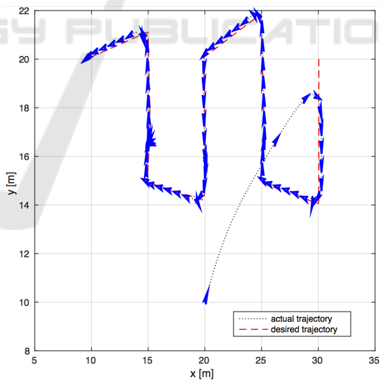

Figure 7: 2D commanded trajectory while identifying forest fires.

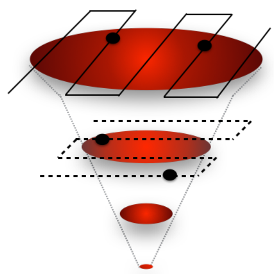

Figure 8: Illustration of two trajectories and communication points of two UAVs.

sends its explored data to the other UAVs using predefined communication points (see an example in Figure 8). From our experimental results there is an improvement of the number of targets localization when UAVs are working together. Additionally, the localization precision of the targets in different depths are better than the onces with the same depth.

The effective performance of the low-level controller while tracking the commanded trajectory is depicted on figures 5, 6 and 7. The simulation study, during the forest fire identification, reveals that heading behavior is significantly aggressive. Thus, it suggests that the proposed decision-based planner is more adapte to the navigation profile of rotorcraft aerial robots. The simulation also shows that a Kinodynamic model is adequate to meet the trajectories provided by the high-level planner.

6 CONCLUSIONS

In this paper we implemented a high-level decision-based planning to localize forest fires using a rotorcraft UAV within an unknown exploration area. The effectiveness of forest fire-detection missions based on UAVs are constrained by the flight endurance of the vehicle. Thus, it is proposed a methodology to avoid exhaustive exploration of the fire zone. Instead, the UAV explores the area based on the perceived data while optimizing the decision related to the exploration. Previous works on high-level task planning are mostly used on terrestrial and underwater robotics. To the best of our knowledge, there are no high level task-planning used on unmanned aerial robotics. In the herein presented proposal, we have implemented a high decisional task-planning combined with a two-level controller (low-level) using an UAV featuring a kinodynamic model. The latter considers a forest fire model to represent its evolution and also incorporates a map containing the perceived and the predicted data of the forest fire. The conducted simulation study exhibit satisfactory performance of the proposed approach applied for rotorcraft UAVs for different depths and in cooperative mode. The obtained results show that the proposed methodology provides encouraging results. Future works include the experimental implementation using a quadrotor vehicle developed locally.

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