Monitoring Atmospheric Phenomena within Low-Altitude Clouds with a Fleet of Fixed-Wing UAVs

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I. Introduction

Atmospheric scientists have been early users of UAVs, from which significant scientific results have rapidly been obtained (*e.g.* [1]). UAVs indeed bring forth several advantages over manned flight to probe atmospheric phenomena: low cost, ease of deployment, possibility to evolve in high turbulences [2], etc. Yet atmospheric phenomena span the three spatial dimensions and evolve over time, and their analysis requires much more data than a single UAV can gather. Fleets of UAVs are the natural solution to gather more and more relevant information, and they can especially collect synchronised observations of a series of distant areas.

This article depicts on-going work on the development of a fleet control approach to probe low-altitude cumulus clouds. From an atmospheric science point of view, there remain numerous uncertainties and even unknowns in the cloud micro-physics models that could be alleviated with the acquisition of a variety of data *within and around* the cloud. Wind currents, pressure, temperature, humidity, liquid water content, radiance, aerosols are data of interest that must be collected with a spatial and temporal resolution of respectively about $10\,m$ and $1Hz$ over the cloud lifespan. Deploying a fleet of UAVs for this purpose raises a series of challenges: exploring the cloud is a poorly informed and highly constrained adaptive sampling problem, in which the UAVs motions must be defined so as to maximize the amount of gathered information and the mission duration.

A wholesome global approach has been defined, which casts the overall problem in a hierarchy of two modeling and decision stages. A macroscopic parametrized model of the cloud is exploited at the higher level to set information gathering goals, possibly with an atmospheric scientist in the loop, to each of which a subset of the UAV team is allocated, considering *e.g.* their current position in the cloud, their on-board energy level, and their sensing capacities (because of payload constraints, the UAVs may not all embark the same sensor suite). These goals typically consist of cloud regions to explore, and are handled by the lower level, which optimizes the selected UAVs trajectories using an on-line updated dense model of the variables of interest.

The article focuses on this latter level. It sketches the modeling and the trajectory generation processes that actively drive a handful of UAVs within a given area, aiming at maximising the information gain while minimizing the energy consumption.

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II. Environment Model

To plan energy-efficient and informative trajectories, a model that represents both the wind currents and the atmospheric variables to measure is required. The accuracy of these information is of course of utmost importance, as it is the dimension that steers the information gathering and that conditions the expectation of the path costs estimates.

The considered context raises two main issues: the size of the three-dimensional space, in which UAVs collect very sparse measurements, and the dynamics of the considered atmospheric phenomena. The only way to be able to predict short term atmospheric conditions from the sparse measurements is to make use of the strong spatio-temporal correlations of the atmospheric processes. Considering the little available knowledge about these, there are no many efficient tools to tackle this problem.

Recent work have shown that Gaussian Processes (GP) can successfully be used to perform spatio-temporal regression in robotics problems. GP is a very general non-parametric framework, where the underlying process is modeled by "a collection of random variables, any finite number of which have a joint Gaussian distribution" [3]. Under this assumption, the process is defined only by its mean and covariance functions. The mean function is often assumed to be zero, but it can be used to set a prior. The covariance function represents similarity between points: given a set of n samples (x, y) and assuming zero mean, the GP $y = f(x)$ is fully defined by the Gram matrix $K_{n,n} = [k(x_i, x_j)]$ of the covariances between the sample points. The choice of the kernel function k conditions the process distribution as it sets a prior on the process properties such as isotropy, stationarity or smoothness. The particularity of the GP model is to provide full predictive distributions over all possible f, whose mean and variance at each point can be interpreted as the process predicted value and associated error.

Until recently, the usage of GP models for online problems has been prevented by prohibitive inference cost in $\mathcal{O}(n^3)$, due to the Cholesky decomposition of the K matrix which must be updated each time new samples are added. Recent algorithmic advances for streaming data and greater computing power spawned several contributions solving online problems in the robotics community [4].

Working with meteorologists, we aim to prove that this method is adequate for mapping atmospheric conditions by assessing its efficiency on realistic data from meso-scale simulations. This work focuses on choosing and comparing appropriate kernel functions to take advantage of domain specific priors, and show that realistic atmospheric variables can successfully be estimated online by a fleet of UAVs (figure 1).

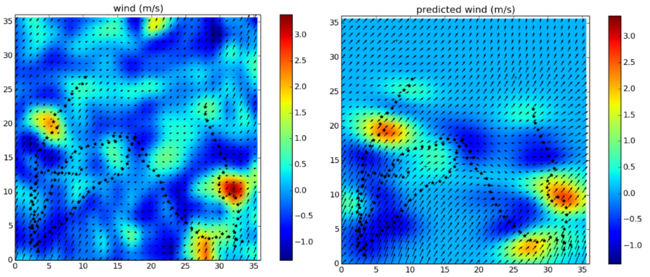

Fig. 1. Illustration of the estimation of the horizontal wind direction and speed provided the application of GP regression using data perceived along two UAVs trajectories (denoted by black stars). Left: ground truth, output of a realistic atmospheric simulation; right: predicted wind.

III. TRAJECTORIES GENERATION

The GP regression scheme reconstructs a local air flow and atmospheric variables map using measurements, from which optimal trajectories that maximize the information gathered can be generated. The motion model of the UAVs assumes a fixed constant speed v_0 with respect to the air. The resultant ground velocity is $v = v_0 + c$, where c is the air speed. The motion for each UAV is then completely characterized by the values of its three directional angles. We do not assume any constraint on the current speed, which can be greater than v_0, and hence define unreachable areas. For the sake of simplicity we consider here the two-dimensional version of the problem, in which only one control angle α determines the UAV motion. Trajectories are generated over a short time horizon ΔT, defined by the frequency at which the GP hyper-parameters are updated. Within this time horizon, we consider m sections of duration dt in which the UAV directions are constant: the trajectory for the robot j is described by the sequence of angles $\alpha_i^{(j)}$, $i \in \{1, ..., m\}$.

We can now formulate the trajectory generation problem as a constrained optimization problem:

$$\underset{\boldsymbol{\alpha}^{(1)},\ldots,\boldsymbol{\alpha}^{(N_r)}}{\text{argmax}} \sum_{t=t_0}^{t_0+\Delta T} U(\mathbf{x}_t^1(\boldsymbol{\alpha}^{(1)}), \ldots, \mathbf{x}_t^{N_r}(\boldsymbol{\alpha}^{(N_r)})) \tag{1}$$

$$s.t. \quad |\alpha_i^{(j)}| \leq \alpha_{max} \quad \forall i, j \tag{2}$$

where $\mathbf{x}_t^{(j)}$ is the position of the UAV j at time t, $U(\cdot)$ is the utility map and N_r is the number of UAVs involved in the mission. To tackle this optimization, we propose a two-step approach: a first phase based on a blind random search in order to have a good trajectories initialization, followed by a gradient ascent algorithm to optimize them. To perform the gradient ascent we adopted a constrained version of the Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm [5], which ensures a faster convergence to a local maximum with respect to classic gradient approximation algorithms. The blind random search is achieved creating a set of feasible trajectories obtained by a constrained random sampling of directions angles α_i, and exploiting the approximated field generated by the GP regression. The trajectories are then evaluated using the local utility map U, as in eq. (1), and the best set of N_r trajectories is the initial configuration for the gradient ascent phase. The presence of the first sampling step is due to the strong dependence of the gradient-based solution on the initial configuration. In this way, even though we only have local convergence guarantees, the probability of getting stuck in local maxima far for the global optimal trajectories is reduced. Figure 2 shows some trajectories obtained in a fictitious two-dimensional current field, that steers the UAVs towards high utility regions while trying to follow the wind direction.

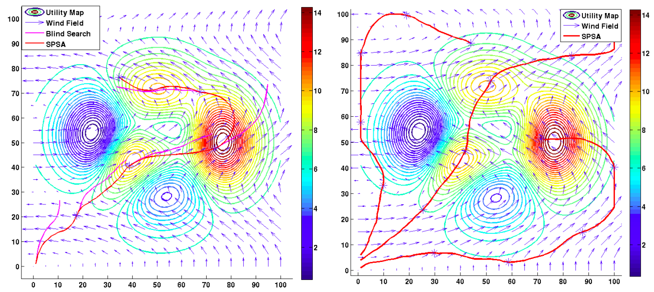

Fig. 2. Left: one UAV is moving in a 2D environment where a scalar utility map and a wind field are defined. The trajectories initialized by a blind search at every time-horizon ΔT are shown in magenta, and the final trajectories provided by the SPSA algorithm are in red. Right: 3 UAVs are steered in the same environment to maximize the gathered information (only the final trajectories are shown).

IV. FUTURE WORK

By integrating tightly the environment modeling and the path planning processes, we hope to achieve a mutually beneficial improvement. Indeed, by taking into account not only the predicted values and errors, but also the shape of the kernel function to drive the path planning algorithm, one should allow the on-line definition of the spatio-temporal scales, adapted to the atmospheric conditions at hand.

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