

Monitoring the Evolution of Cumulus Clouds with a Fleet of UAVs

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Outline

- 1 Introduction: the SkyScanner project
- 2 Modeling the environment
 - Problem Statement
 - Gaussian processes: an introduction
 - Links between models and planning
- 3 Trajectory generation
 - Problem Formulation
 - Optimization Method
- 4 Experiments & Results
 - Meso-NH simulations: a realistic environment
 - Path planning: preliminary results
- 5 Summary and prospects

Mapping the micro-physical properties of cumulus clouds

Spatio-temporal evolution of μ -physical properties of a cumulus ?



Issues :

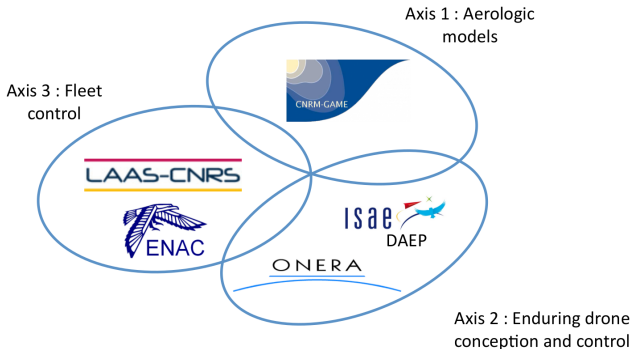
- Size, at the base: $\approx 100\text{m}$, height: $\approx 1\text{km}$
- Short lifespan $\approx 20\text{min}$ to 1h

Solution:

- A plane ?
- A drone (UAV) ?
- \Rightarrow A fleet of UAVs

The SkyScanner project

Project financed by the STAE foundation



- CNRM: Model of the cloud μ -physics
- ISAE: Conception of an automatically optimized vehicle
- ONERA: Optimized control architecture
- ENAC: 3D Wind estimation, the Paparazzi autopilot
- **LAAS: Path planning and mapping**

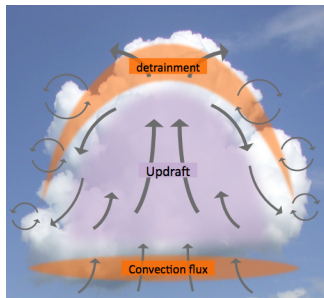
Objectives of a mission

A fleet (>2) of UAVs has to collect data inside a cumulus cloud

Objectives:

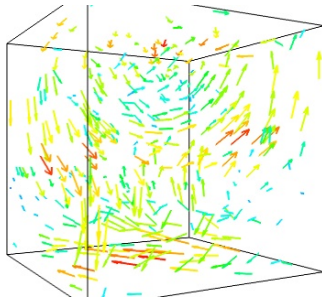
- (Maximum) duration: 1h
- Identify the different areas and characteristic variables of the cloud:
altitude of the base, height, strength of the ascending currents,...
⇒ parametric, conceptual model
- Map the evolution of some μ -physical parameters in predefined areas
⇒ (dense) statistical model

A hierarchy of models



parametric model

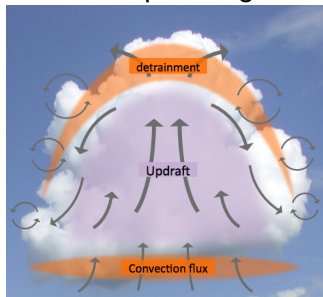
Ex: $updraft = f(diam, height)$



stochastic regression model

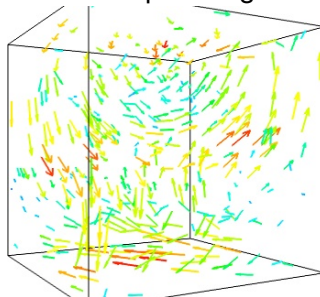
Two-stage planning approach

Task planning



$\Delta T \approx 1\text{min}$

Path planning



$\Delta T \approx 10\text{sec}$

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Modeling the environment

Issues:

- Reconstructing a 3D+Time map from punctual and sparse measurements
- Size of a cumulus

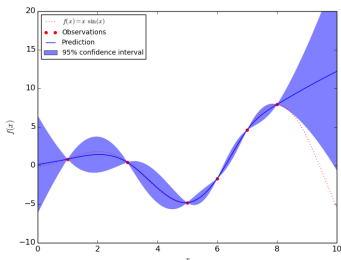
We use *Gaussian Processes* to solve this *regression* problem

«A *Gaussian Process* is a collection of random variables, any finite number of which have a *joint Gaussian distribution*.», CE Rasmussen et CKI Williams, *Gaussian Processes for Machine Learning (2006)*).

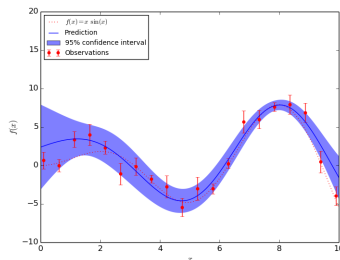
Gaussian \Rightarrow entirely defining by its **mean** and **covariance**

Gaussian Process Regression (GPR)

- + Abundance in literature (although more statistics - big data)
- + Continuous world, prediction of the error
- +/- Cost of inference: $\mathcal{O}(n^3)$ building model, $\mathcal{O}(n^2)$ each inference
- Choosing kernels, slow hyper-parameters optimization



Noiseless GPR



GPR with noise

Problem statement

Given some samples, we wish to reconstruct the underlying process f

Definition

$$\begin{aligned} f : \mathbb{R}^{n_{features}} &\longrightarrow \mathbb{R} \\ X &\longmapsto y = f(X) \end{aligned}$$

In our case, $n_{features} = 4$

→ the features are the space-time locations of the samples

Definitions

Definition

$$f \approx \mathcal{GP}(m(\mathbf{X}), k(\mathbf{X}, \mathbf{X}))$$

$m(\mathbf{x})$: expectation, **zero** in most cases

$k(\mathbf{x}, \mathbf{x}')$: covariance or **kernel** (function)

Definition

Let (\mathbf{X}, Y) be an ensemble of n samples in $R^k \times R$, then:

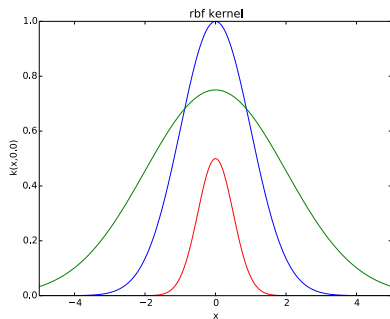
$$m(\mathbf{x}) := 0 \text{ (zero mean)}$$

$$\Sigma := k(\mathbf{X}, \mathbf{X}) + \sigma_{noise}^2 I$$

Σ is the $n \times n$ covariance matrix accounting for a Gaussian noise of variance σ_{noise}^2

Kernel families

How to choose the covariance function (kernel) ?



- Choose a kernel family
→ sets a prior (stationarity, periodicity...)
- Set hyper-parameters
→ optimization

Squared Exponential kernel family

Inference

Theorem

Inference: for a given sample x_ in R^K*

$$\bar{y}_* = k(\mathbf{x}_*, \mathbf{X})\Sigma^{-1}\mathbf{y}$$

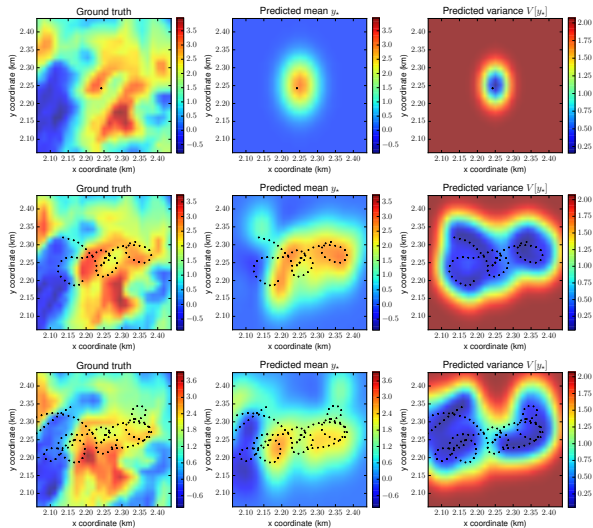
$$\mathbb{V}(y_*) = k(\mathbf{x}_*, \mathbf{x}_*) - k(\mathbf{x}_*, \mathbf{X})\Sigma^{-1}k(\mathbf{x}_*, \mathbf{X})^\top$$

\bar{y}_* is the *mean*, $\mathbb{V}(y_*)$ the *variance* at point \mathbf{x}_* of the functions represented by the GP conditioned by the \mathbf{X} previous samples

Cost of inference:

- $\mathcal{O}(n^3)$ for inverting Σ
- $\mathcal{O}(n^2)$ for subsequent predictions

Illustration of the mapping process



Information gathering

Is a planned path interesting in terms of gathered information ?

Goal: maximize information given a criterion on the model

- minimizing the covariance between samples:
 - D: maximize differential entropy (log-det of Σ^{-1})
 - T: maximize trace of Σ^{-1}

Let m new samples \mathbf{X}_{new} and $\Sigma_{\mathbf{X}}$ the $n \times n$ covariance matrix between the n previous samples \mathbf{X} :

$$\Sigma_{\mathbf{X}_{new}|\mathbf{X}} = k(\mathbf{X}_{new}, \mathbf{X}_{new}) - k(\mathbf{X}_{new}, \mathbf{X})\Sigma_{\mathbf{X}}^{-1}k(\mathbf{X}_{new}, \mathbf{X})^{\top}$$

We then compute directly D and T from the conditional covariance $\Sigma_{\mathbf{X}_{new}|\mathbf{X}}$

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Problem Formulation

Task to achieve

Maximize the information gain within an area of interest while minimizing the energy consumption

- Centralized approach: ground station and no communication issues
- Aircraft dynamics:
 - Constant airspeed
 - Constrained control inputs: turn radius R and power input P_{in}

Problem Formulation

Task to achieve

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From an objective to an optimization function

Three criteria to optimize during the mission:

- Energy:

$$U_E^{(j)}(t_0, \Delta T) = 1 - \frac{1}{P_{in}^{max} \Delta T} \sum_{t=t_0}^{t_0+\Delta T} P_{in}^{(j)}(t) dt$$

- Information Gain:

$$U_I(v) = \max \left(0, \min \left(1, \frac{v + v_{Tb} - 2v_{Tp}}{2(v_{Tb} - v_{Tp})} \right) \right)$$

- Region of Interest:

$$U_G^j(t_0, \Delta T) = \frac{d_b(X_{t_0+\Delta T}^j) - d_b(X_{t_0}^j)}{V_{zmax} \Delta T}$$

Total Utility Function:

$$U_{tot} = w_E U_E + w_I U_I + w_G U_G$$

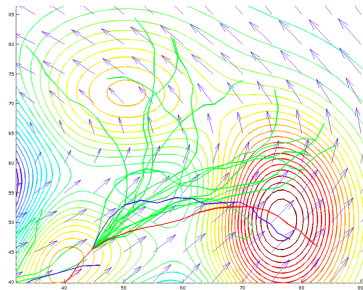
Approach

- Finite (short) horizon $\Delta T \sim 20s$
 - Model reliability
 - Computational complexity
- Planning in control space
 - Currents strongly affect navigation (unfeasible movements, unreachable areas, etc.)
- The trajectories are discretized and defined as a sequence of control inputs $\{\mathbf{u}_0, \mathbf{u}_{dt}, \dots, \mathbf{u}_{\Delta T-dt}\}$

Approach

Two-step optimization scheme:

- Blind random sampling for trajectories initializations
- Constrained stochastic gradient ascent algorithm (SPSA) with local convergence guarantee



Stochastic Gradient Approximation

Stochastic Gradient Approximation by Simultaneous Perturbation
Stochastic Approximation (SPSA) algorithm:

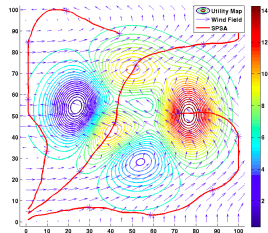
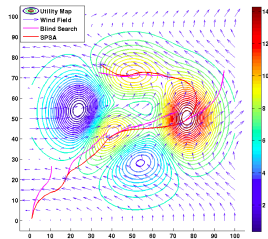
$$\mathbf{u}_{k+1} = \Pi(\mathbf{u}_k + a_k \hat{\mathbf{g}}(\mathbf{u}_k))$$

$$\hat{\mathbf{g}}_k(\mathbf{u}_k) = \begin{bmatrix} \frac{U(\mathbf{u}_k + c_k \Delta_k) - U(\mathbf{u}_k - c_k \Delta_k)}{2c_k \Delta_{k1}} \\ \vdots \\ \frac{U(\mathbf{u}_k + c_k \Delta_k) - U(\mathbf{u}_k) - c_k \Delta_k}{2c_k \Delta_{kN}} \end{bmatrix}$$

$$a_k > 0, c_k > 0, a_k \rightarrow 0, c_k \rightarrow 0, \sum_{k=0}^{\infty} a_k = \infty, \sum_{k=0}^{\infty} \frac{a_k^2}{c_k^2} < \infty$$

An illustrative example

- Artificial 2D wind field
- Fictitious utility function
- The goal is to maximize the utility collected along the path

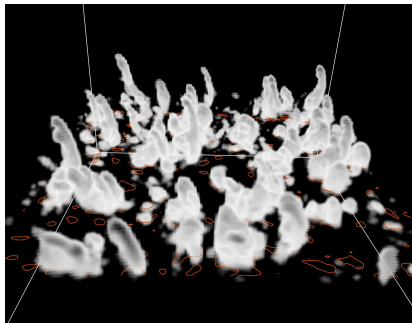
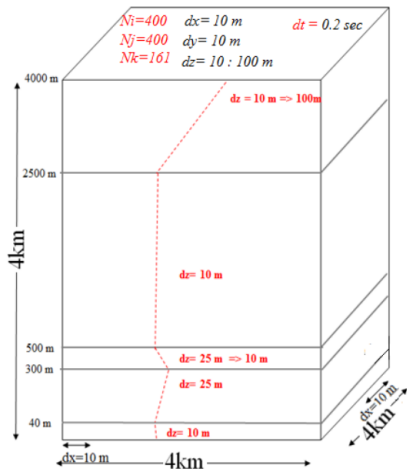


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Meso-NH simulation: example

Simulation grid



Still frame from a simulation. In shades of grey the liquid water content, in orange the $+0.5 \text{ m} \cdot \text{s}^{-1}$ upwind isometric curves

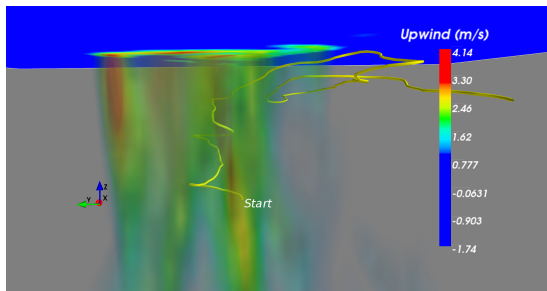
Meso-NH simulations

Meso-NH: Large scale simulations, model created and validated by meteorologists. Simulations provided by the CNRM.

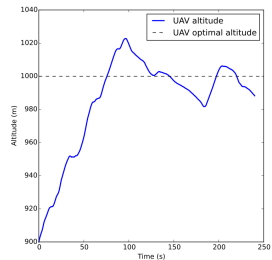
- Scenario = cumulus cloud field arising from daily convection
- Simulates all micro-physical properties (incl. wind)...
- 700 MB per frame
- at one frame per second
- One hour → 2.5 TB
- ...weeks of computing on the meteo-france cluster

→ Statistical study of the environmental model (pending)

One agent in a static wind field



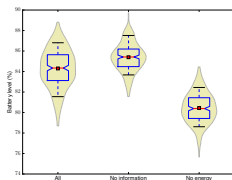
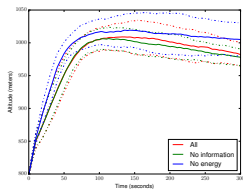
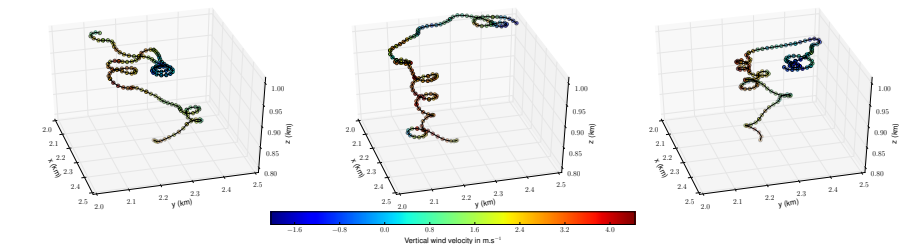
UAV trajectory



Altitude of the UAV during the flight

A. Renzaglia, C. Reymann, and S. Lacroix, "Monitoring the evolution of clouds with UAVs", ICRA 2016

Three agents in a dynamic wind field



Trajectories, altitude profiles
and battery levels for three
UAVs flying simultaneously

C. Reymann, A. Renzaglia, F. Lamraoui, M. Bronz and S. Lacroix, "Adaptive Sampling of Cumulus Clouds with a Fleet of UAVs",
Autonomous Robots, under review

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Summary

SkyScanner@LAAS, today:

- A **realistic** meteorological **simulation**
- A **stochastic environmental model** using GPR
- A simple **utility function** integrating energy and IG criteria
- A **stochastic path planning** algorithm

⇒ The first iteration of a complete simulation environment

Prospects

Environment model:

- better handling of the time dimension
- developing a conceptual cloud model
- embedding prior knowledge into the GP model

Planning:

- proper multi-criteria utility function
- using Paparazzi which integrates a realistic FDM
- task planning

Real experiments

Questions ?

Thank you for your attention

More information about the SkyScanner project at:
<https://www.laas.fr/projects/skyscanner/>