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Autonomous Search of Atmospheric CBR Release using Mobile Robotics: An Information Theoretic Framework

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- General framework for atmospheric release search and reconstruction
- Source term estimation based method
  - Bayesian estimation
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Introduction

- Atmospheric hazardous materials, especially Chemical, Biological and Radiological (CBR) related releases are becoming an increasing concern.
- Such incidents may include volcanic eruptions, nuclear accidents and CBR attacks or accidental releases.



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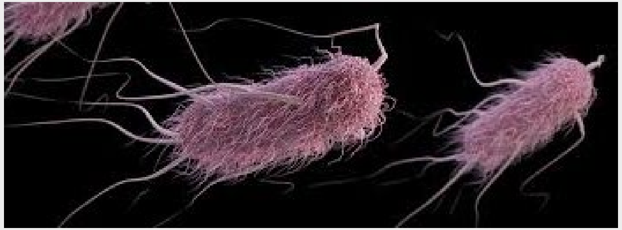
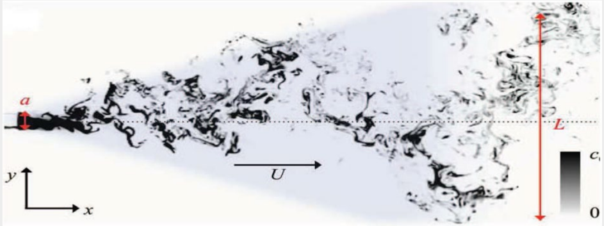
Introduction

- Research Goals:
  - Establish the understanding of the contamination in the environment in an effective and safe way
- Autonomous robotic solutions:
  - Keep operators safe
  - Require less expertise to operate
  - Can explore inaccessible areas
  - Can be deployed in larger numbers

Research challenges:

- Finding an emitting source is not as easy as climbing concentration gradients, as sensor observations are noisy and sporadic.
  - Inspired from nature, an information based approach is adopted



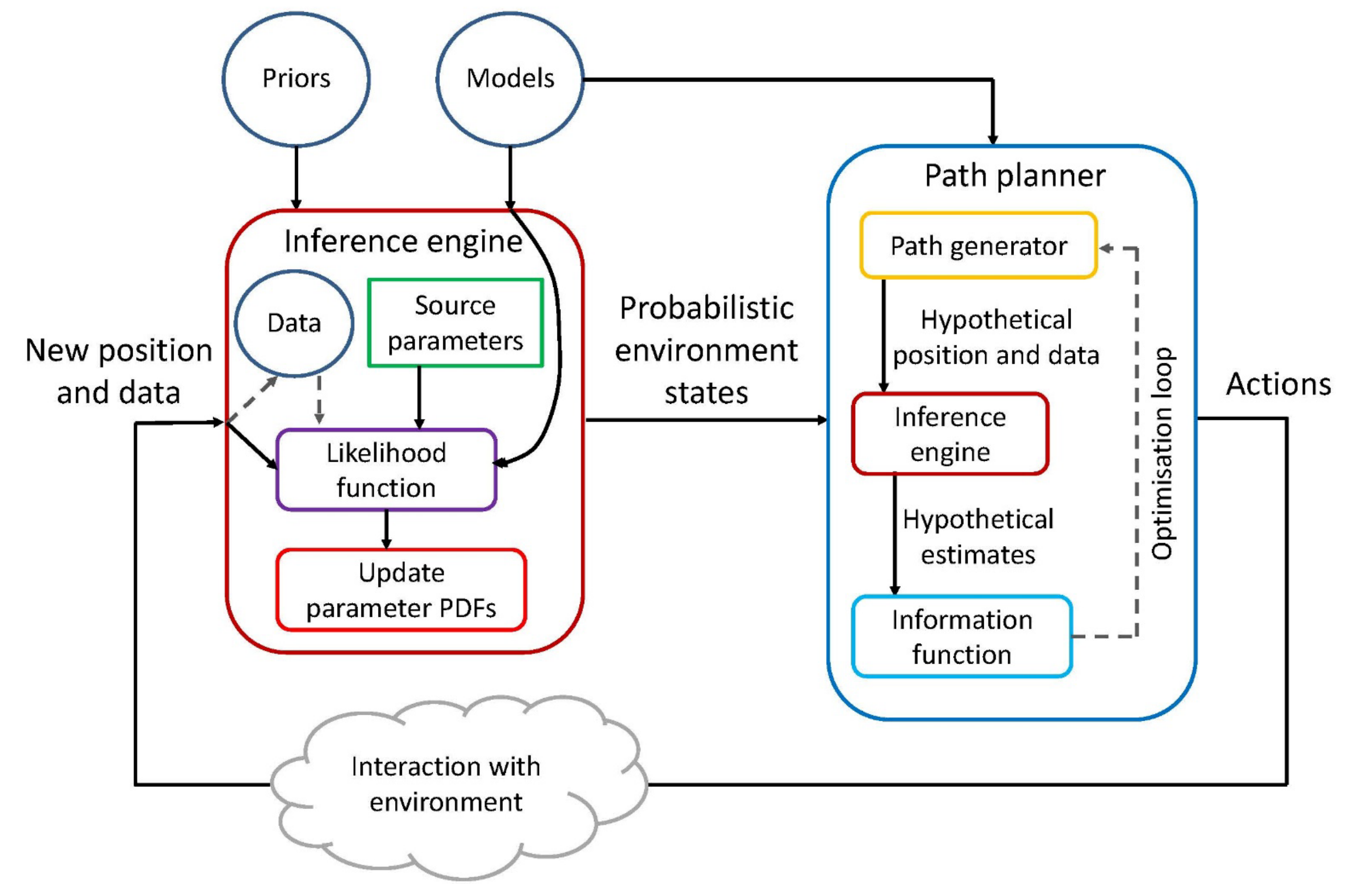


- Other engineering challenges
  - Cluttered, obstacle rich environments
  - Improve sample efficiency to overcome limited flying time
  - Constraints on computational power

Information-theoretic framework

- Basic principle
  - Representing the environment by using a mathematical model
    - Atmospheric transportation and dispersion (ATD) model
      - Parameters in the model, a.k.a. source term, need to be estimated
    - Data driven models, e.g., Gaussian process
  - Informative path planning
    - Exploit the current understanding of environment to make sampling decisions
      - By maximising the information gain
    - New measurements acquired at chosen sampling locations are in turn used to update or learn the model of the environment

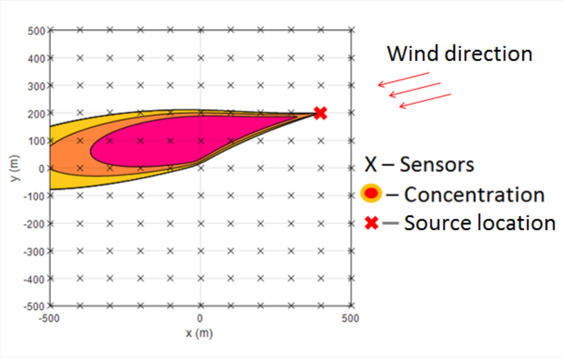
Information-theoretic source search and reconstruction framework

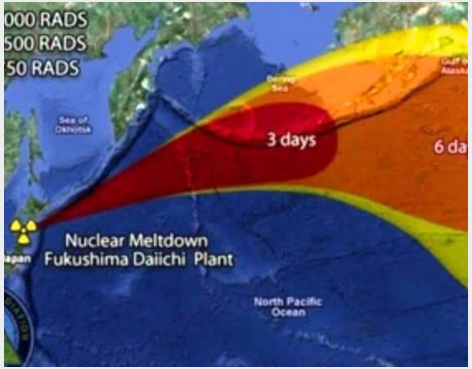


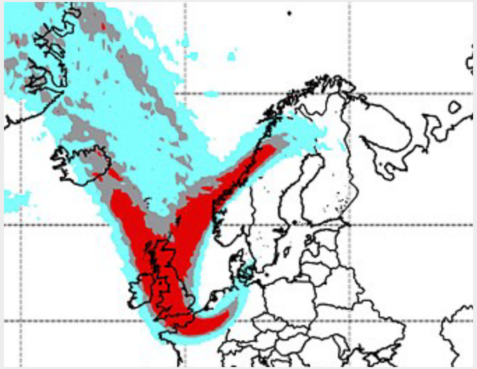
Source term estimation using particle filter

- Atmospheric transport and dispersion models can be used to indicate the release source and the forecast of its dispersion.

- The Source term in ATD
  - Source location (x, y, z)
  - Emission rate (Q [grams/s])



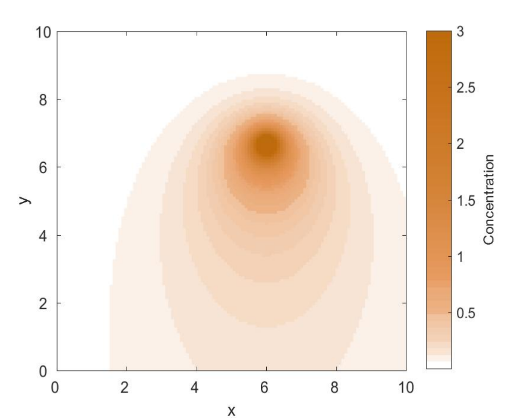




Algorithm formulation: environment modelling

- Environment model: Dispersion model is required to define link between the concentration data and source term (also the observation model)
  - Turbulent advection-diffusion equation is used, that takes into account: Average lifetime of particles, diffusivity, the wind vector and sensor area.
  - Parameters include Met uncertainty: wind strength, direction

$$C\left(\mathrm{p}_k|\Theta_k\right) = \frac{q_s}{4\pi d_s||\mathrm{p}_k - \mathrm{p}_s||}\exp\left[\frac{-||\mathrm{p}_k - \mathrm{p}_s||}{\lambda}\right] \times \exp\left[\frac{-(x_k - x_s)u_s\cos\phi_s}{2d_s}\right]\exp\left[\frac{-(y_k - y_s)u_s\sin\phi_s}{2d_s}\right]$$



Algorithm formulation

- Source term of release is defined as follows: $\Theta_k = [\mathbf{p}_s^\top \quad q_s \quad u_s \quad \phi_s \quad d_s \quad \tau_s]^\top$
  - Cartesian coordinates of the source $\mathbf{p}_s = [x_s \quad y_s]^\top \in \Omega$ in meters (m).
  - Release rate/strength of the source $q_s \in \mathbb{R}^+$ in grams per second (g/s).
  - The wind speed $u_s \in \mathbb{R}^+$ in meters per second (m/s) and direction $\phi_s \in \mathbb{R}$ in radians (rad).
  - Diffusivity of the hazard in air $d_s \in \mathbb{R}^+$ in meters squared per second (m^2/s).
  - Lifetime of the emitted material $\tau_s \in \mathbb{R}^+$ in seconds (s).
- A robot is collecting point observations $\mathbf{z}_{1:k} = \{z_1, \ldots, z_k\}$
  - at known locations $\mathbf{p}_{1:k} = \{\mathbf{p}_1, \ldots, \mathbf{p}_k\}$

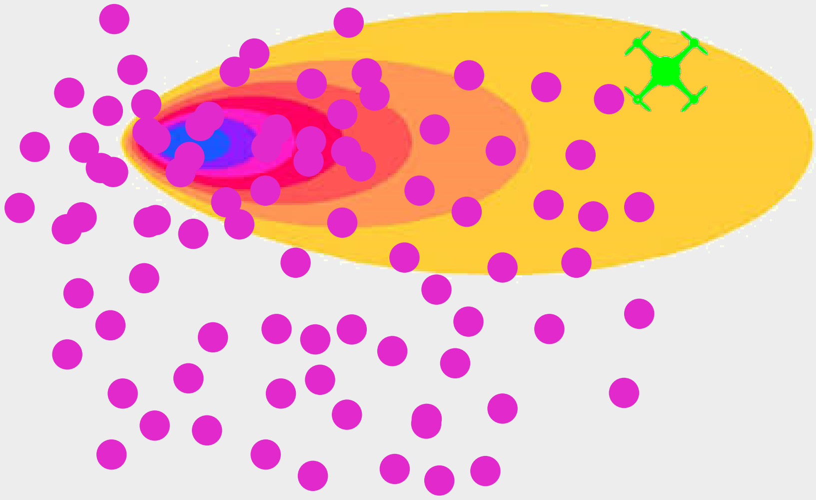
Algorithm formulation: inference engine

- Inference: Bayes theorem will update probability densities of the source parameters θ in response to new data d.
- A probabilistic approach is preferred for scenarios where there are large amounts of uncertainty that can be modelled mathematically.
- The strength and location of the hazardous source and other parameters are estimated using the sequential Monte Carlo framework.

$$P(\theta|d,I) = \frac{P(\theta|d)P(\theta|I\ )}{P(d|I)}$$

$$\theta = [X_0\ Y_0\ A_0\ U_0\ \phi_0\ D_0\ \tau_0]^{\mathrm{T}}$$

Conceptual solution – source term estimation



- Bayesian estimation is performed using a sequential Monte Carlo algorithm.
- Random samples (Pink dots) with low weights are resampled around highly weighted ones.
- One of the great challenges from experiments is in sensor modelling.

Algorithm formulation

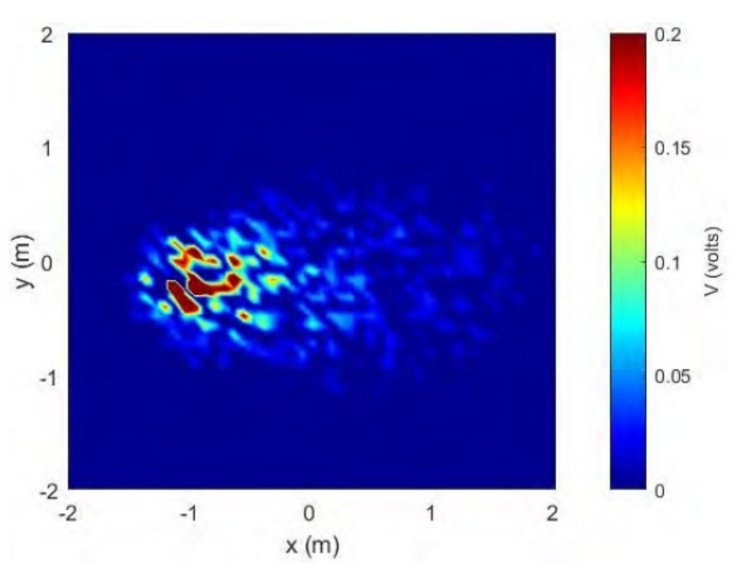
- Dispersion model (converted into sensor voltage reading)

$$V(\mathbf{p}_k, \Theta_k) = \frac{A_0}{4\pi d_s ||\mathbf{p}_k - \mathbf{p}_s||} \exp\left[\frac{-||\mathbf{p}_k - \mathbf{p}_s||}{\lambda}\right] \times \exp\left[\frac{-(x_k - x_s)u_s \cos\phi_s}{2d_s}\right] \exp\left[\frac{-(y_k - y_s)u_s \sin\phi_s}{2d_s}\right]$$

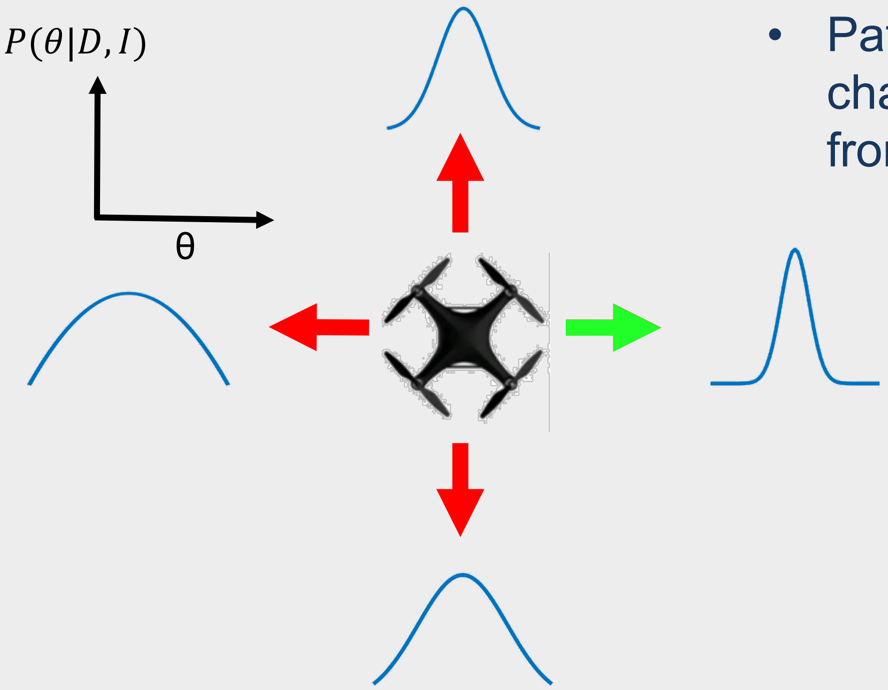
$$\lambda = \sqrt{\frac{d_s \tau_s}{1 + (u_s^2 \tau_s)/(4d_s)}}.$$

- Likelihood function
  - Considering probability of detection
  - Gaussian noises

$$p(z_k|\Theta_k) = (1 - P_d) \cdot \mathcal{N}(z_k; 0, \underline{\sigma}_k) + P_d \cdot \mathcal{N}(z_k - V(\mathbf{p}_k, \Theta_k); 0, \bar{\sigma}_k)$$



Conceptual solution - Planning



- Path planning is based on the expected change in what we know about the source from a manoeuvre.
  - Consider new locations to take a measurement from
  - At each position:
    - Given what we know
    - Estimate what we expect to see
    - Approximate what I expect to learn (KL divergence)
  - Move to most informative choice

Algorithm formulation: Planning

- Bayesian estimation for source term:

$$p(\Theta_{k+1}|\mathbf{z}_{1:k+1}) = \frac{p(z_{k+1}|\Theta_{k+1})p(\Theta_{k+1}|\mathbf{z}_{1:k})}{p(z_{k+1}|\mathbf{z}_{1:k})}$$

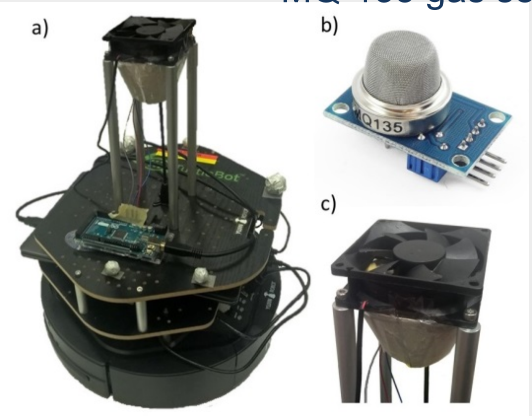
$$p(z_{k+1}|\mathbf{z}_{1:k}) = \int p(z_{k+1}|\Theta_{k+1})p(\Theta_{k+1}|\mathbf{z}_{1:k})\, \mathrm{d}\Theta_{k+1}.$$

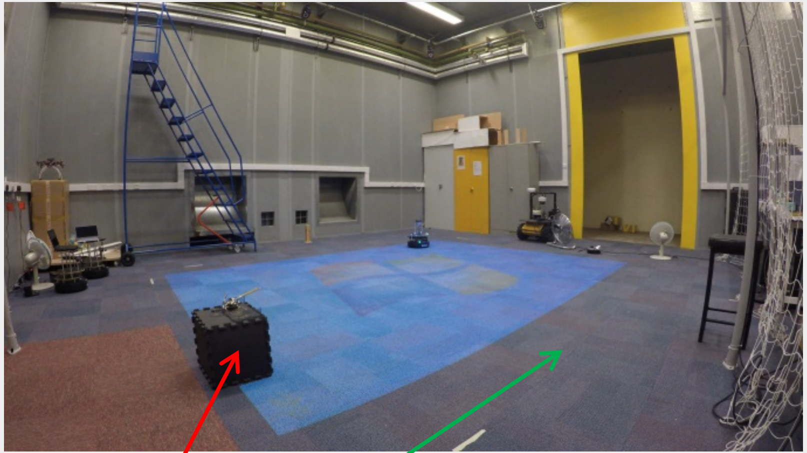
- Decision marking
  - Admissible set of actions $\Psi_k = \{\uparrow, \downarrow, \leftarrow, \rightarrow\}$
  - Reward function to capture information gain $\Upsilon(z_{k+1}(\mathbf{a}_k))$
  - Future measurement is unknown, therefore the decision is made based on the expected reward

$$\mathbf{a}_k^* = \arg \max_{\mathbf{a}_k \in \Psi} \mathbb{E}\left[\Upsilon(\hat{z}_{k+1}(\mathbf{a}_k))\right]$$

Feasibility study

MQ-135 gas sensor





Smoke source

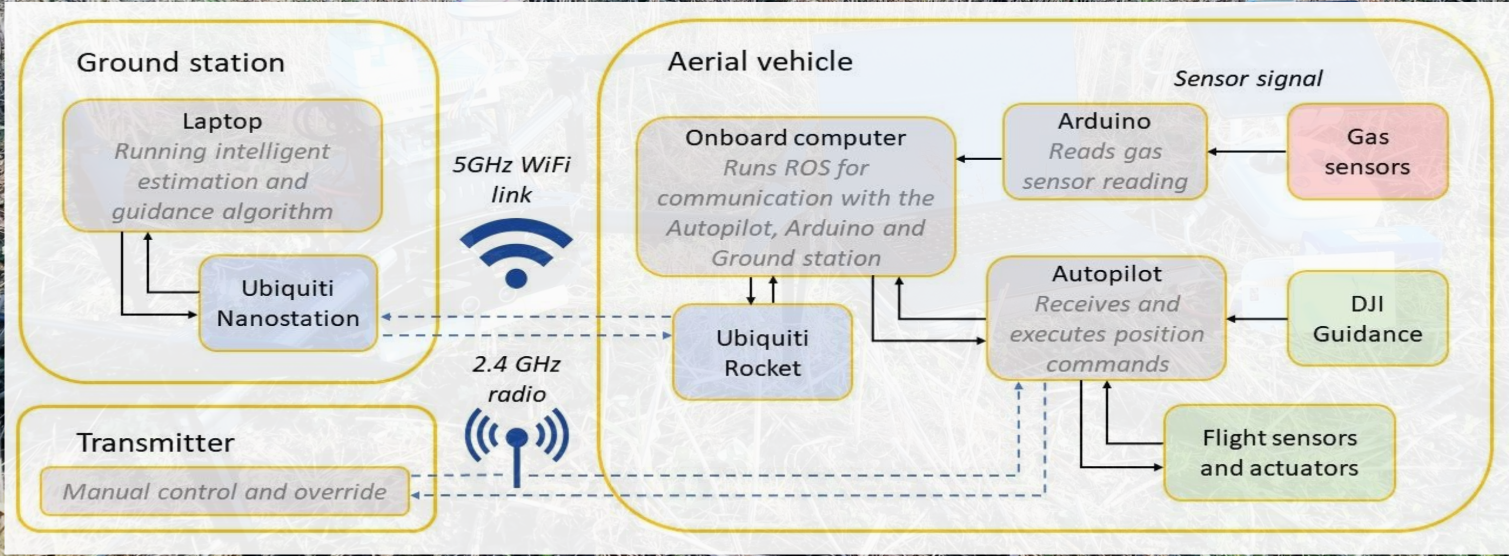
Wind direction

M. Hutchinson, C. Liu and W. Chen, "Information-Based Search for an Atmospheric Release Using a Mobile Robot: Algorithm and Experiments," in *IEEE Transactions on Control Systems Technology*, vol. 27, no. 6, pp. 2388-2402, Nov. 2019, doi: 10.1109/TCST.2018.2860548 .

Summary

Example runs of the autonomous search and source term estimation experiments with varying source release strengths (number of burning incense sticks).

Deployment on a small UAV



Hutchinson, M, Liu, C, Chen, WH. Source term estimation of a hazardous airborne release using an unmanned aerial vehicle. *J Field Robotics*. 2019; 36: 797–817. https://doi.org/10.1002/rob.21844

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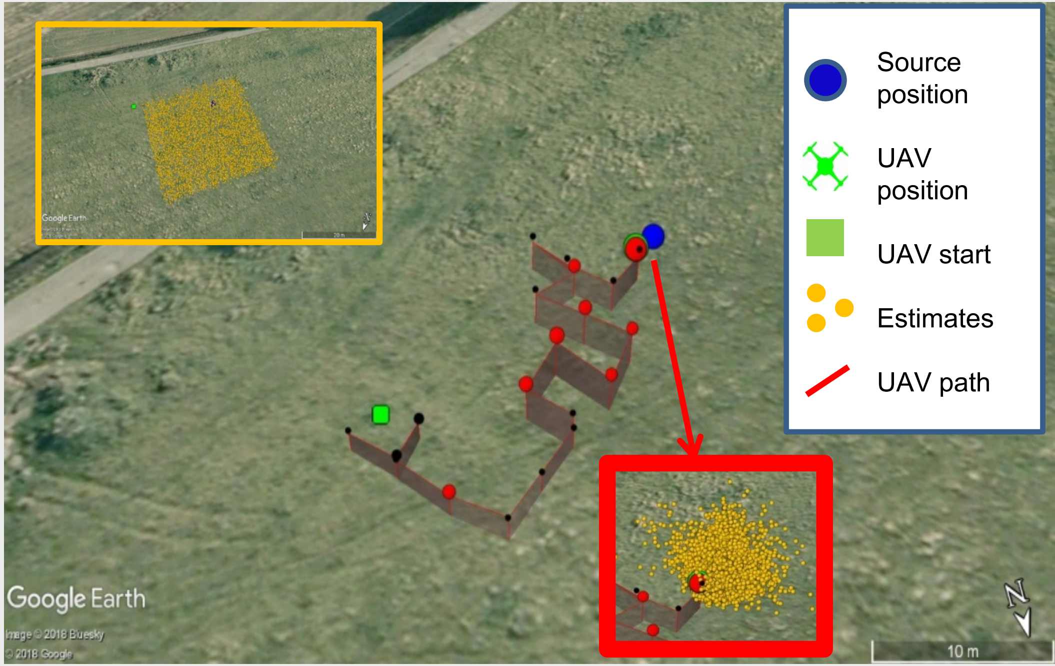
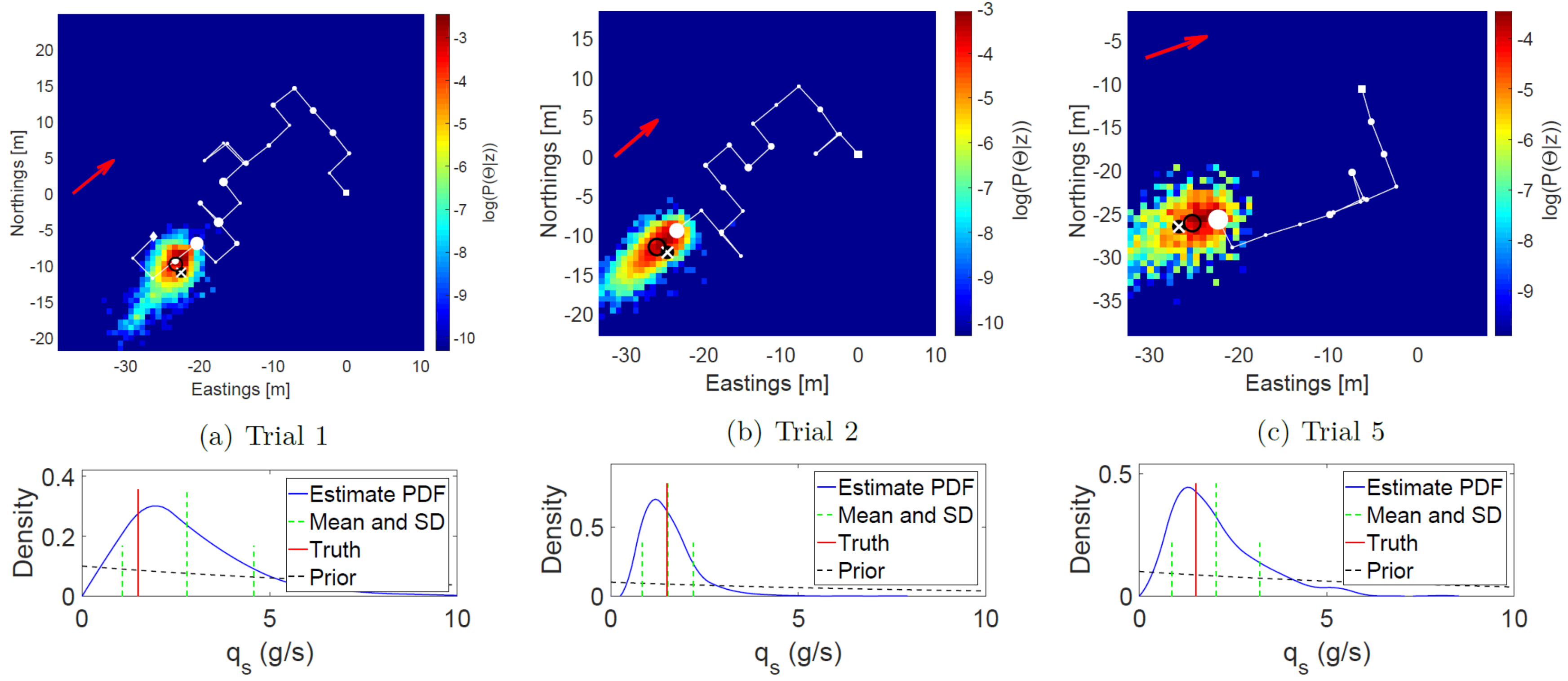
Experiment setup

Acetone source, release roughly 1.5grams/s





(d) Trial 1 emission estimate

(e) Trial 2 emission estimate

(f) Trial 5 emission estimate


M. Hutchinson, C. Liu, P. Thomas and W. -H. Chen, "Unmanned Aerial Vehicle-Based Hazardous Materials Response: Information-Theoretic Hazardous Source Search and Reconstruction," in *IEEE Robotics & Automation Magazine*, vol. 27, no. 3, pp. 108-119, Sept. 2020, doi: 10.1109/MRA.2019.2943006.
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Further work on autonomous search

- Assumptions on the dispersion model
  - Steady wind
  - Open space
- More work is required for cluttered environments
- Balance between exploitation and exploration
- Larger scale

A dual control concept

- Balancing Exploitation and Exploration
  - Dual control cost function

$$\min_{\mathbf{u}_k} J(\mathbf{u}_k) = \min_{\mathbf{u}_k} \mathbb{E}_{\Theta}\left[\mathbb{E}_{\hat{z}_{k+1}}\left[\|\mathbf{p}_{k+1|k} - \mathbf{s}\|^2 | \mathcal{Z}_{k+1|k}\right]\right]$$

subject to

$$\mathbf{p}_{k+1|k} = \mathbf{p}_k + \mathbf{u}_k$$

$$\mathbf{u}_\mathbf{k} \in \mathcal{U}$$

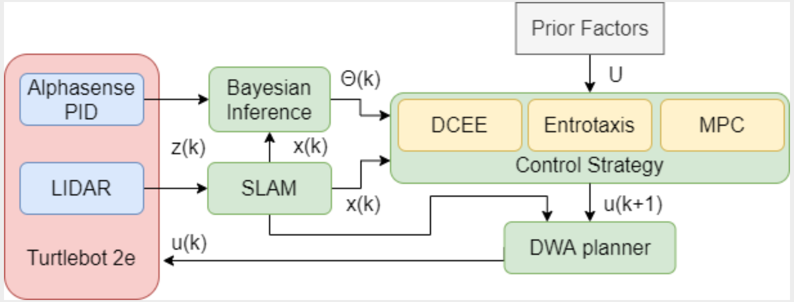
where $\mathcal{Z}_{k+1|k} := \{\mathcal{Z}_k, \hat{z}_{k+1}\}$.

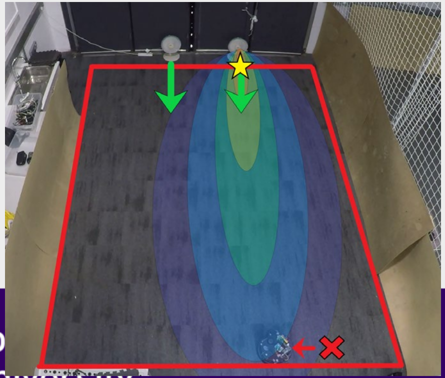
$$J(\mathbf{u}_k) = \|\mathbf{p}_{k+1|k} - \bar{\mathbf{s}}_{k+1|k}\|^2 + trace(Q_{k+1|k})$$

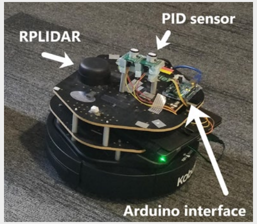
Wen-Hua Chen, Callum Rhodes, Cunjia Liu, Dual Control for Exploitation and Exploration (DCEE) in autonomous search, Automatica, Volume 133, 2021, 109851.
https://doi.org/10.1016/j.automatica.2021.109851

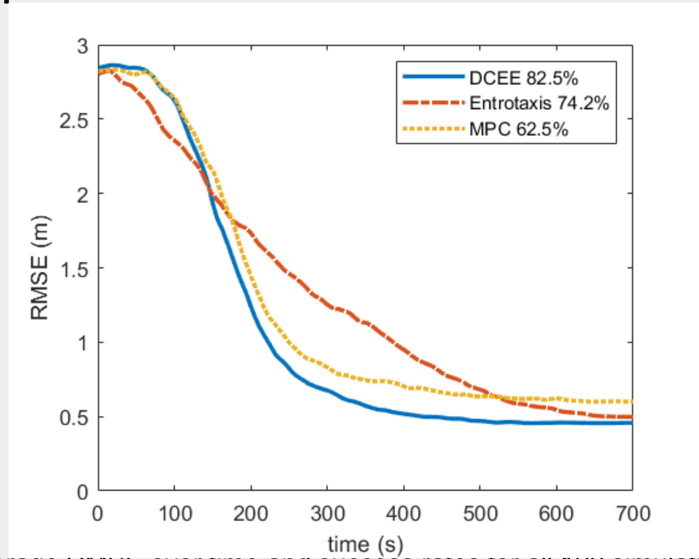
A dual control concept

- Balancing Exploitation and Exploration
  - Verification using experiments









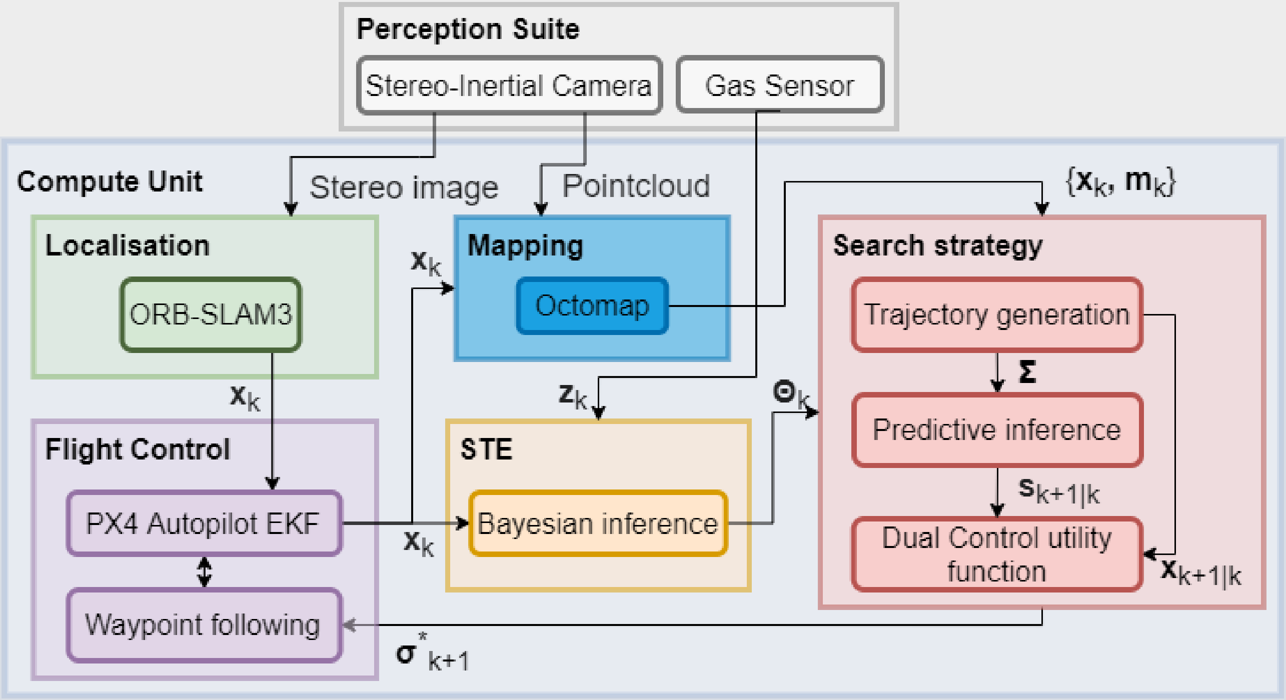
Average RMSE over time and success rates for all 120 simulation runs

Average RMSE over time and success rate for each control method across both experimental configurations

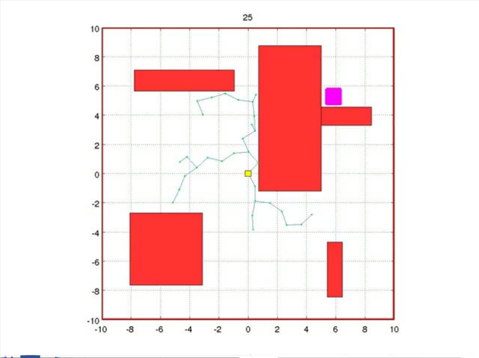
Search in cluttered environment

- Technical Challenges:
  - GPS denied environment for UAVs
  - Collision avoidance function
  - Efficiency and diversity in path planning

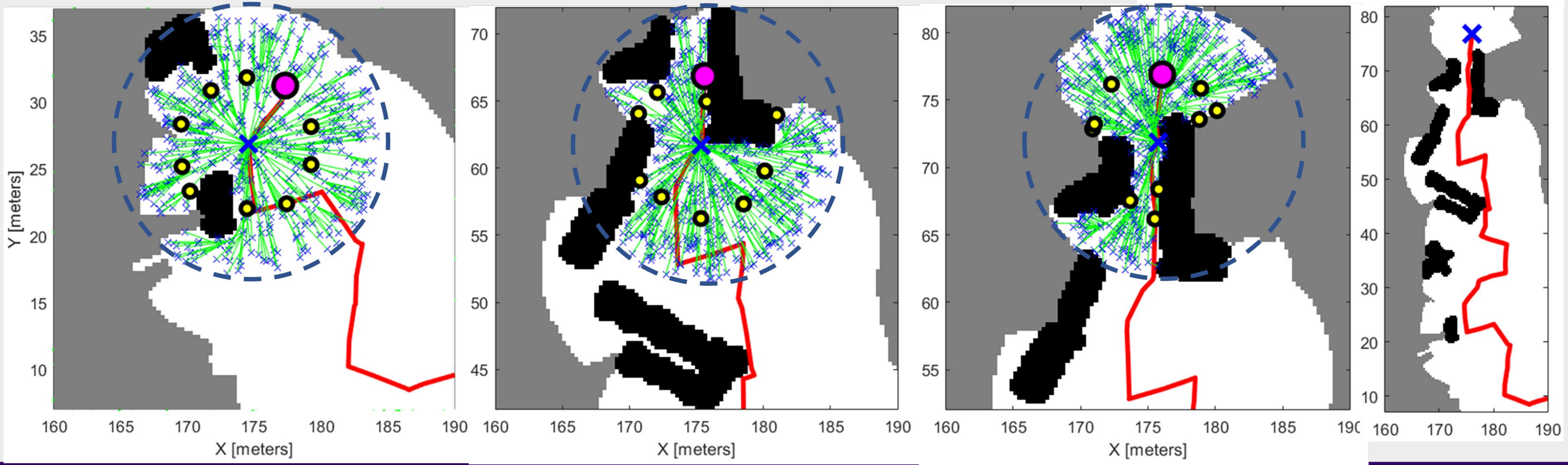
System Architecture



Trajectory Generation – RRT*

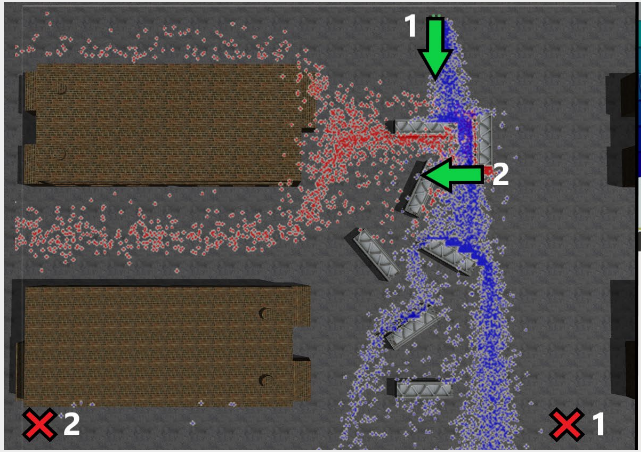


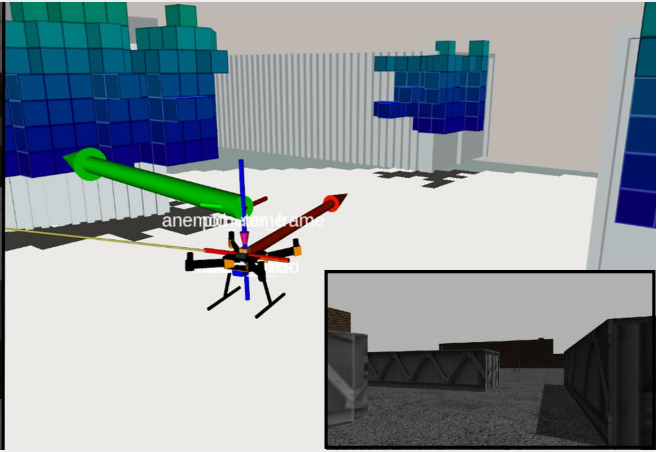
Apply RRT* first to check traversibility of DCEE samples, then pass to DCEE function for utility evaluation

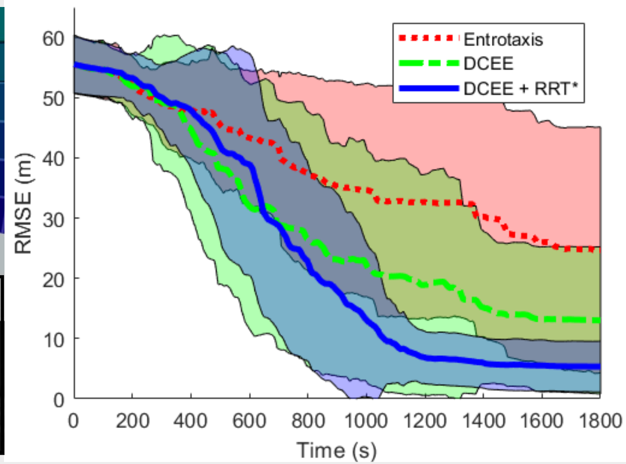


Sim results

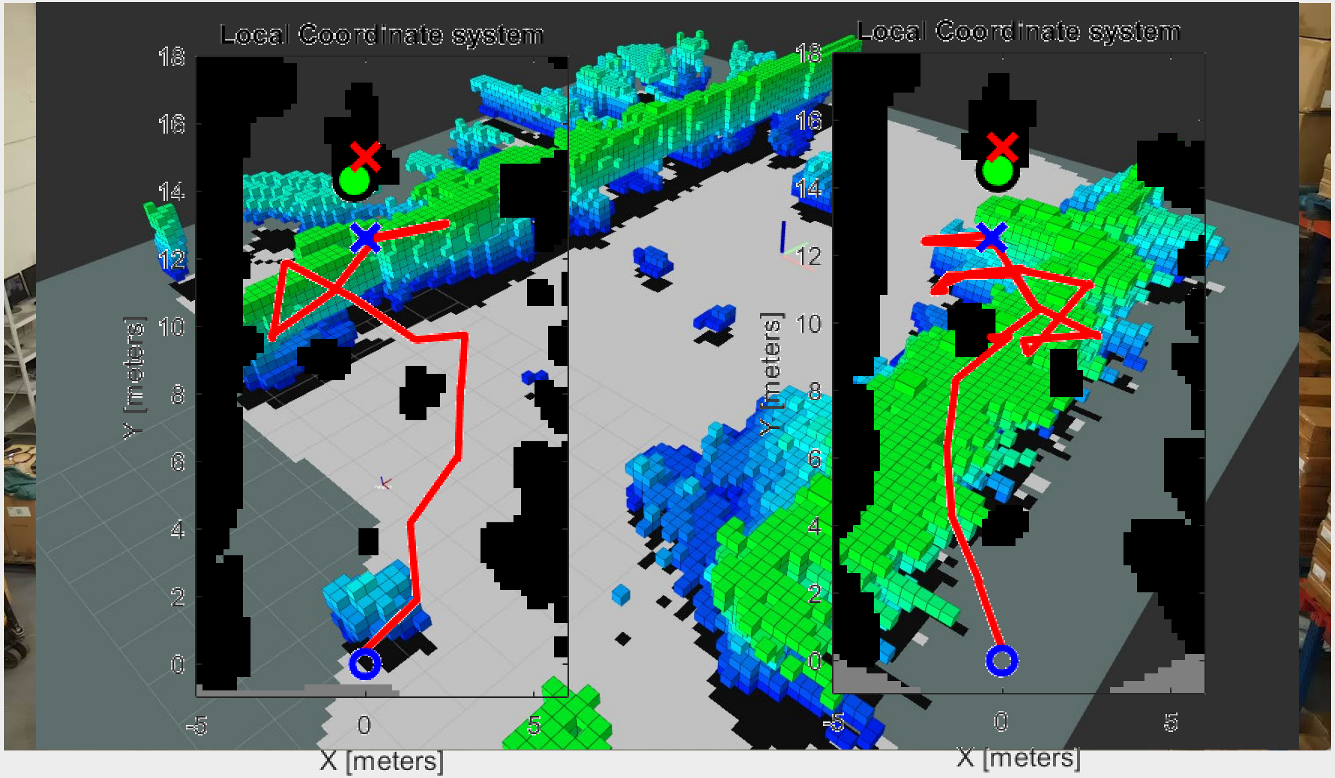
Algorithm		Source (s) and start location (x)			
		s_1, x_1	s_1, x_2	s_2, x_1	s_2, x_2
Entro	MST	1029	1045	1098	1207
	SR	40	40	40	40
DCEE	MST	**594**	1521	976	943
	SR	60	40	80	60
DCEE + RRT*	MST	600	**1024**	**991**	**830**
	SR	**100**	**100**	**100**	**100**







Experiment verification




Questions?