Fugitive Methane Detection and Localization With Small Unmanned Aerial Systems: Challenges and Opportunities

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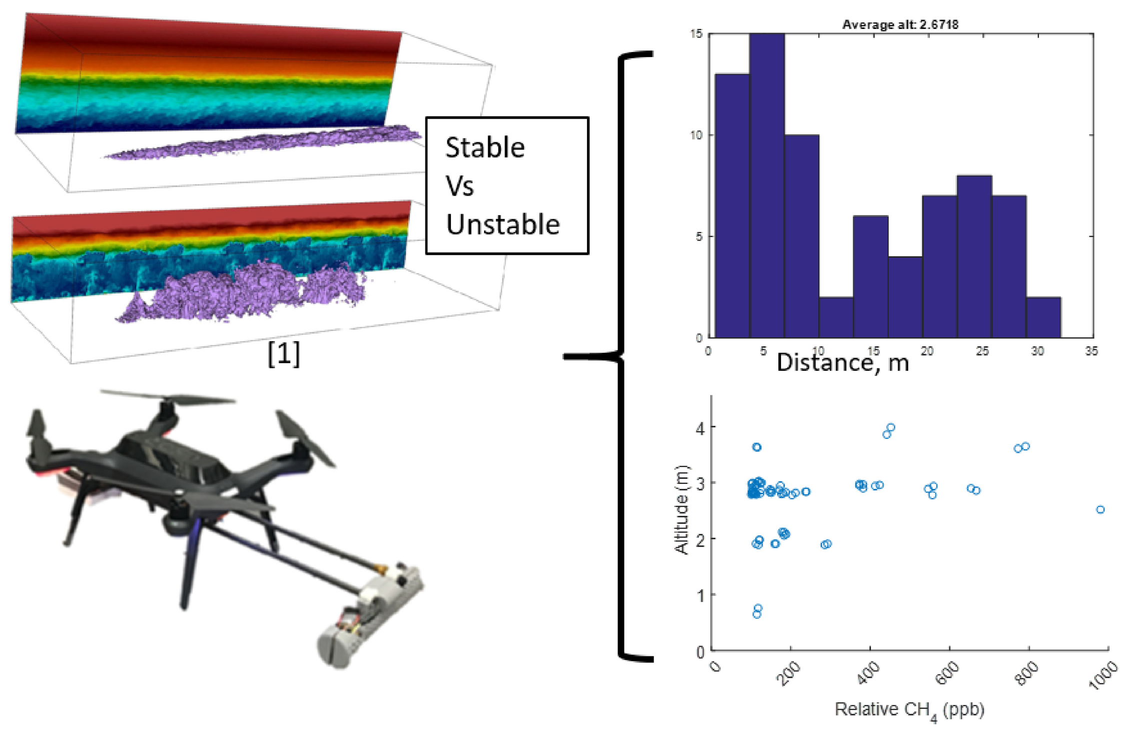
Introduction

Natural gas is one of our main methods to generate power today. Utility companies that provide this gas are tasked with maintaining and surveying leaks. These leaks are referred to as fugitive methane emissions and detecting these fugitive gases can be pivotal to preventing incidents such as the San Bruno explosion, killing 8 and injuring dozens due to a gas leak going undetected. Recently, using NASA technology onboard low cost vertical takeoff and landing (VTOL) small unmanned aerial systems (sUAS) we can detect fugitive methane at 1 ppb (parts per billion) levels.

Challenges in Detection

General challenges include: FAA regulations (no flights over people), battery life, and complex dynamic plume behavior. Factors that impact detection can be: propeller wash, sensor placement, wind, and mechanical/electrical noises. Even distance to source and flight altitudes can change the probability of detection (Sigmoid like) scaling with topology and atmospheric stability. Localization by CFD approaches are costly making real-time estimations and visualizations difficult.



Quasi-Steady Inversion

Following the work by Matthes et al (2005), Carslaw (1959), and Roberts (1923) the solution to a single point source advection diffusion equation (ADE) can be solved for a dynamic system approximately by making a quasi-steady state assumption if the variance and transient behavior of the wind small. W_0 is the Lambert function.

$$\frac{\partial C}{\partial t} - D\frac{\partial^2 C}{\partial x_i^2} + v\frac{\partial C}{\partial x_i} = 2q_0\delta(t-t_0)\delta(x_i - x_{i0})$$

$$\bar{C}(\bar{x}_i, x_0, q_o)_i = \frac{q_0 \exp(\frac{\bar{v}(\bar{x}_i - x_0)}{2D})}{\pi^{\frac{2}{3}} Dd}$$

$$d_i(C_i, x_0, q_0) \approx \frac{2D}{\bar{v}} W_0\left(\frac{\bar{v}q_0}{4\pi D^2 C_i} \exp\left(\frac{v}{2D}(\bar{x}_i - x_0)\right)\right)$$

$$\min_{q_0, x_0} : \sum_{i,j=1}^{m} (y_{0,i}(x_0,q_0) - y_{0,j}(x_0,q_0))^2$$

Adaptive Search Model

In the foraging literature the Levy walk has been shown to be effective at searching sparse environments. However, Brownian motion is more efficient in dense areas. This adaptive search model [5] can switch dynamically from Levy to Brownian based on finding targets using tumble probability $P(x(t))$, $x(t)$ is governed by the stochastic differential equation (SDE) below

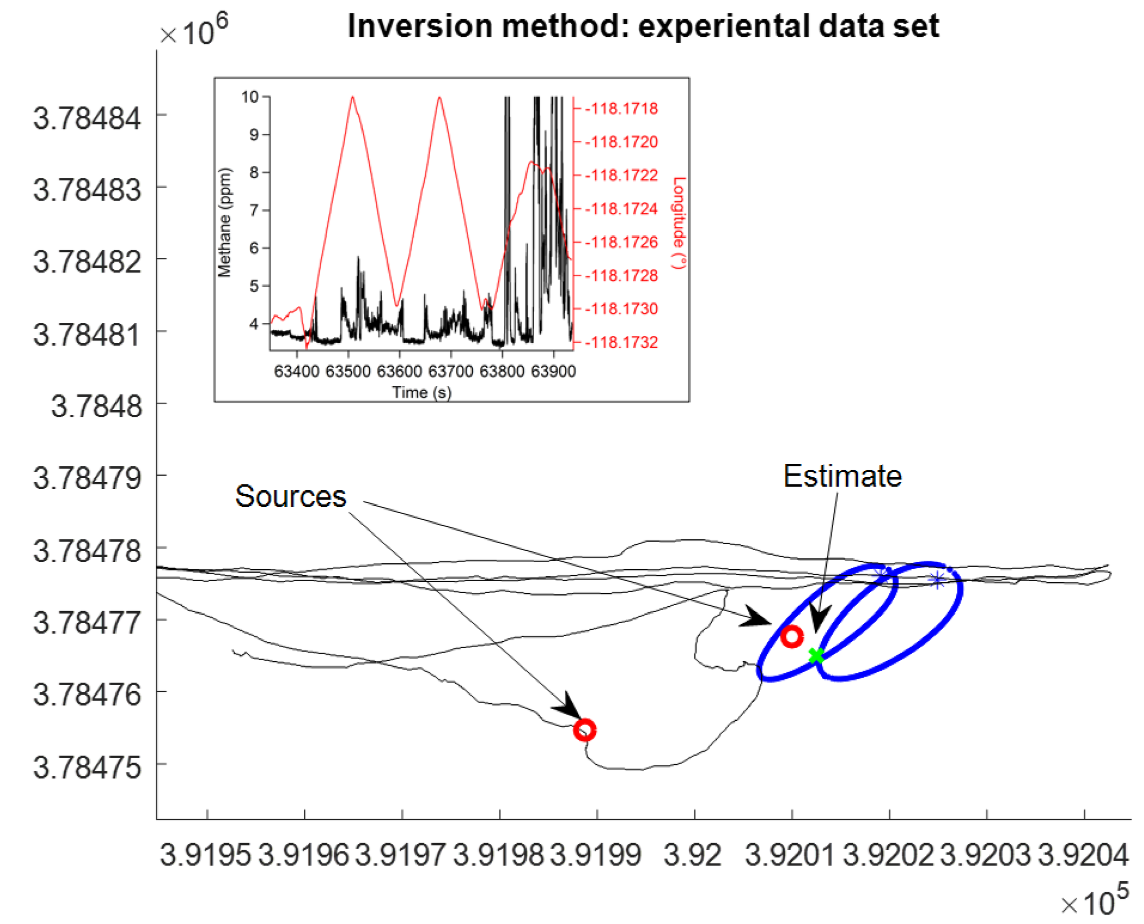
$$P(x(t)) = e^{-x(t)}, \quad 0 \le x \le 5$$

$$\dot{x} = -\frac{\partial U}{\partial x}A + \epsilon, \begin{cases} U = (x-h)^2, \epsilon : \begin{cases} H = \frac{1}{2}, \mathrm{N}(0,\sigma) \\ H \neq \frac{1}{2}, \mathrm{fGn} \end{cases} \\ A = \max(A_{min}, \alpha(t)) \end{cases}$$

$$\alpha_k = C_\alpha \alpha_{k-1} + k_t F \begin{cases} F = 1, \text{found target} \\ F = 0, \text{otherwise.} \end{cases}$$

we extend [5] by adding, fGn, defined as $Y_j = B_H(j+1) - B_H(j)$ and fraction Brownian motion is given below.

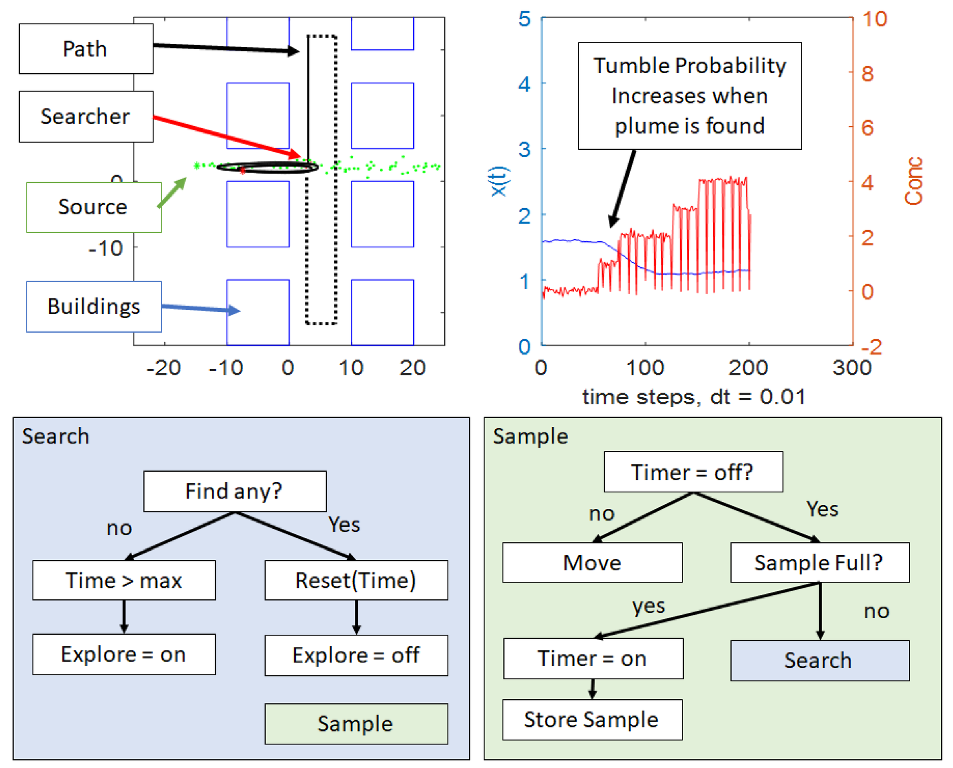
Experimental Results

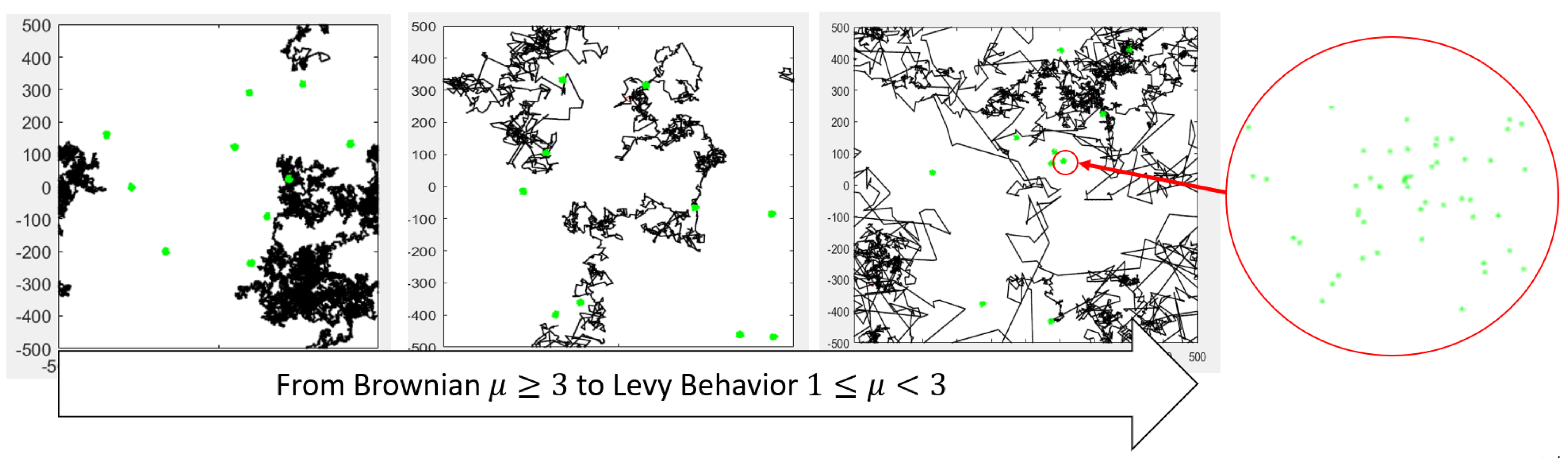


Using the quasi-steady inversion method on experimental data we can see the results from just two samples (blue) in the presence of two sources (red). Only taking a small section of raw data from each longitudinal pass we can approximate the source (green) from our measurement with the OPLS [3].

Adaptive Search and Localization

The adaptive search model has shown to adjust from Brownian motion to Levy walks in a 2D random search. By reducing the problem to a 1D path problem (i.e. survey route) adding decision trees and modeling fugitive gas with a small time scale filament model [4] we have the opportunity to optimize random search for application. Gather enough information to form a sample(s) to use in the inversion method for a Zeroth order approximation of source localization (x_0,y_0) and quantification (q_0).





$$B_H(x) \approx \sum \phi(x-y)B(\Delta y) \qquad \phi(x) = \frac{\Gamma(H+1-d/2+||x||)}{\Gamma(||x||+1)\Gamma(H+1-d/2)} \approx \frac{||x||^{H-d/2}}{\Gamma(H+1-d/2)}$$

Future Research

This work hopes to optimize this adaptive search strategy efficiency $\eta = N/L$ (N is the number of targets found and L is the total distance traveled) through transition parameters (C_α, A_{min}, and k_t) the potential (h), and the choice of noise (i.e. Gaussian or fGn) by means of evolutionary algorithms. Furthermore, we want to answer how the level of noise σ and how the Hurst parameter H, stochastically shift the tumble probability through $x(t)$. Once we have an optimal model we look to compare with current methods (i.e. Zig-Zag, spiral surge [2]), and other gradient or flux based approaches (stochastic gradient descent, fluxotaxis, infotaxis etc.).

References

[1] Matheou et al. *Environ Fluid Mech.*, 2016.

[2] Li et al. *Int. Conf. on Rob. and Biomim.*, 2009.

[3] Smith et al. *ICUAS Miami.*, 2017.

[4] Farrell et al. *Env. Fluid Mech.*, 2002.

[5] Nurzaman et al. *PLos ONE*, 2011.