DERIVING OPTIMIZED UAV FLIGHT PATHS TO LOCATE METHANE EMISSIONS POINT SOURCE USING MACHINE LEARNING ALGORITHMS AND GAUSSIAN PLUME MODELING

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Research Objective

Determine the optimal UAV (Unmanned Aerial Vehicle) flight path to locate a methane plume's point source.

Background

Since the 2015 Paris Agreement, when multiple countries agreed to reduce their greenhouse gas (GHG) emissions and achieve net zero by 2050, interest in GHG emissions monitoring has risen. However, the widely used calculation-based estimations for GHG emissions were criticized for being inaccurate, increasing the need to validate existing GHG inventories using measurement-based solutions.

UAVs are known for being able to monitor real-time emissions while accounting for spatial-temporal variations. Yet, to effectively monitor emissions within a limited timespan across a large 3D space, determining the flight path that can most efficiently and effectively detect plumes and measure concentrations is critical. Unfortunately, no studies have found an algorithmic way of optimizing a UAV's flight path. Before exploring emissions monitoring, however, the first step is to make sure that the UAV can locate an unknown emissions point source in the shortest time possible.

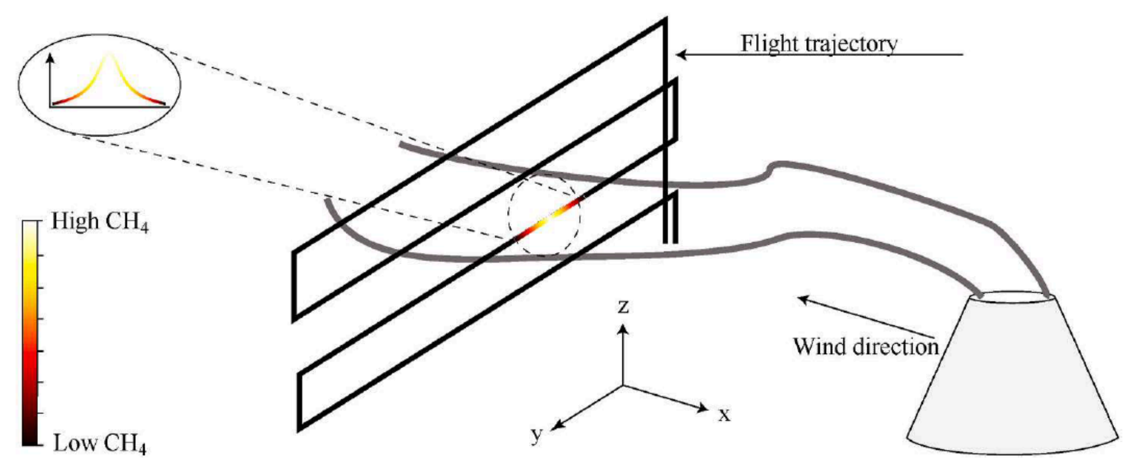

Figure 1: an example flight path design used for plume navigation (Yao 21)

Methodology

The data used to train our algorithm comes from Large Eddy Simulations (LES), known to be more accurate than traditional modeling given its high temporal-spatial resolution and its ability to simulate the dynamic behavior of plumes without the need for time-averaged fields or steady-state assumptions.

The LES provided us with data of a 3D space at different points in time. To train our data, we selected perturbation pressure, base state pressure, perturbation potential temperature, and wind direction components as training features. For the label, we converted the methane concentration data to parts per million (ppm). We then trained the data using different open-source machine learning models via MATLAB, the most promising being the fit linear regression model. Finally, we used the trained model to predict methane concentrations over a 3D space.

Starting at a random coordinate within the plume, we used the greedy search algorithm to find the position with the highest concentration, which we assumed to be the plume center. Based on the measurements made within the surrounding area of the plume center, we implemented the Gaussian Plume Model to derive the point source.

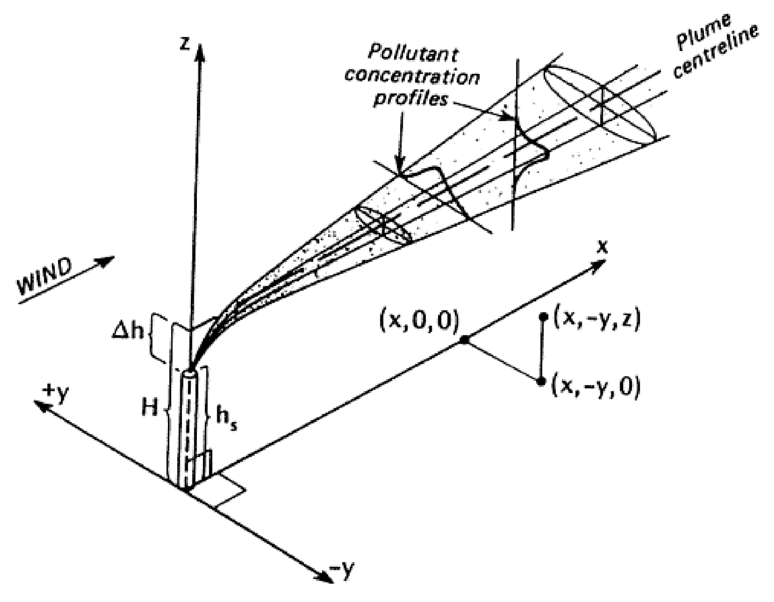

Figure 2: Gaussian Plume Model diagram.

Results & Discussion

We have not tested our model on a site yet, which will happen in the future. To quantify the result, we will simulate multiple flights, measure the distance between the predicted source and the actual source to calculate error, and keep track of flight times, which can be used to compare against traditional, non-algorithmic UAV flight designs.

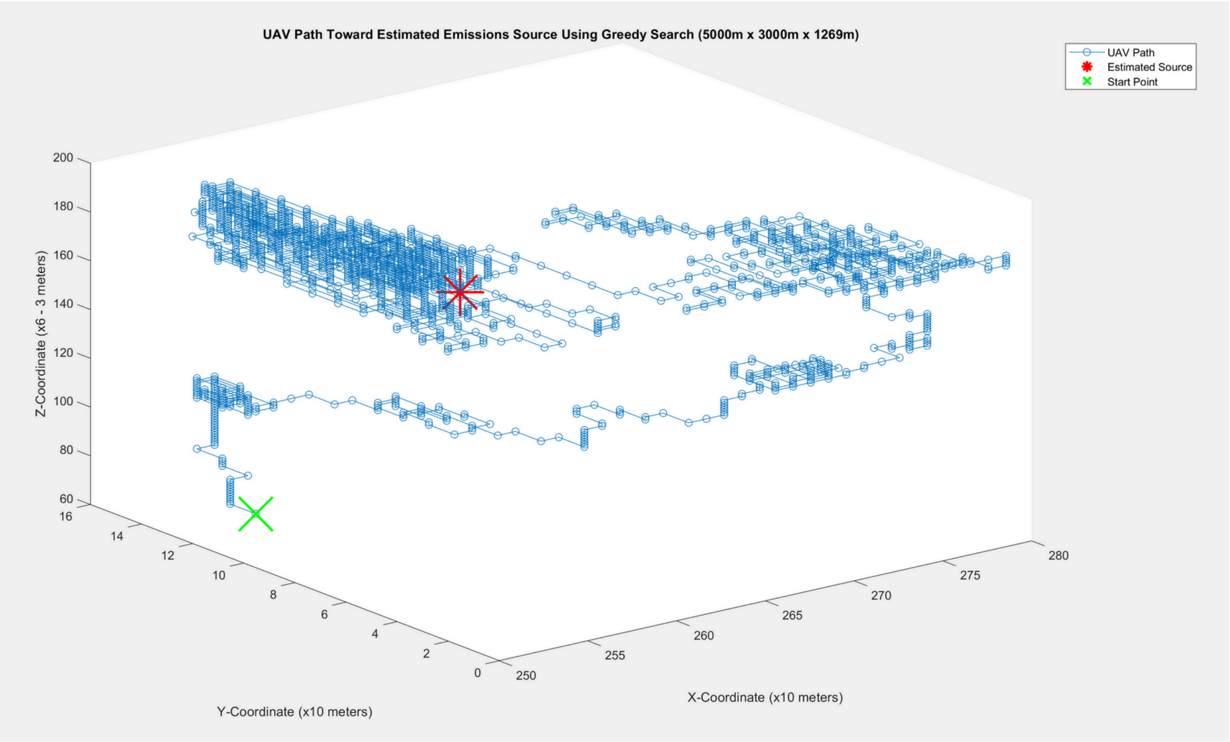

Figure 3: UAV flight path, derived using the algorithm in "Methodology"

It is important to address our approach's limitations. There were many assumptions made when implementing the Gaussian Plume Model to locate the point source, such as wind speed, source strength, dispersion coefficients, and stack height, which could hinder the results. In addition, the greedy search algorithm does not guarantee finding the point with the highest predicted concentration, nor is the point with the highest concentration guaranteed to be the plume center, despite the fact that the statistical likelihood for both of the above scenarios is very high.

Finally, predicting concentrations for a single 3D space, while useful when one does not know the concentrations of a site, does not account for temporal variations of a plume overtime. Therefore, the design is subject to improvement. Instead of limiting the flight path to a 3D space, we can plan the UAV's next step by looking at the LES data for our neighboring coordinates a few instances ahead of the current instance. To improve efficiency, we can also look over a very large area to plan out the UAV's first step, then shrink the observation space for every new step being made until the plume center is found.

Conclusion

- As of 8/4/2024, we designed a UAV flight path that uses greedy search to navigate through a 3D space using predicted methane concentrations to find the plume center. Then, the Gaussian Plume Model was used to derive the point source of emissions
- The model predicting methane concentrations over a 3D space was trained using large eddy simulation data through a fit linear regression
- We will improve our algorithm to account for the plume's temporal variations. Once the algorithm is finalized, site testing will be required for validation

References

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