WS 2024-2025, SMT-ROB, DISAL-SP196 Project Summary

Gas Source Localization with Gaussian Markov Random Fields

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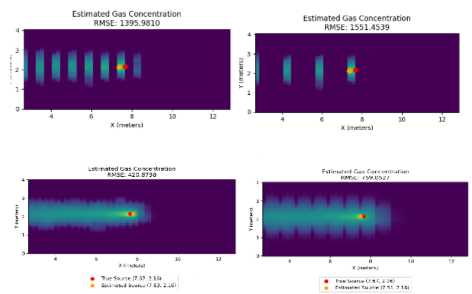
The localization of gas sources in hazardous environments presents a crucial challenge in various applications, including industrial safety and environmental monitoring. Mobile robots equipped with gas sensors can significantly enhance safety by autonomously identifying and mapping gas sources. Traditional Gas Source Localization (GSL) approaches struggle with complex environments due to the stochastic nature of gas dispersion and the influence of wind and obstacles. To address these challenges, this project explores the application of Gaussian Markov Random Fields (GMRFs) for gas distribution mapping and source localization. More specifically, it focuses on the method proposed by Rhodes et al [1] that introduce a structurally aware GMRF-based real-time 2D and 3D gas distribution mapping approach using Gaussian Belief Propagation. This project was structured in two phases: first, an in-depth study of this method to understand its theoretical foundations and implementation, and second, an evaluation of its performance and comparison it to the Kernel DMV method.

Gaussian Markov Random Fields (GMRFs) provide a powerful framework for modeling spatial dependencies in GDM and GSL tasks. By representing the environment as a graph, where nodes correspond to spatial locations (grid cells) and edges capture dependencies between neighboring points, GMRFs enable efficient probabilistic inference. This structure allows for the integration of environmental factors such as obstacles, enhancing the accuracy of gas concentration estimation. Gaussian Belief Propagation (GaBP), a local message-passing algorithm used for inference in GMRFs, provides a computationally efficient alternative to traditional solvers. Unlike direct inversion methods, GaBP propagates local information across the graph, allowing real-time adaptation to new measurements. To evaluate this method, we tested it on pre-recorded gas concentration measurements from an environment with different obstacle configurations and gas source locations. This adaptation enabled performance evaluation across various scenarios and comparison with the Kernel method.



Gas plume estimation for different spasticity of measurements (top row: Kernel, bottom row: GaBP)

Results showed that GBP effectively reconstructs gas distribution maps with higher accuracy compared to traditional Kernel Density Estimation methods, particularly when measurements are sparse but no particular higher accuracy for gas source localization. However, the important computational complexity compared to the Kernel method remains a limitation. Performance analysis indicated that the accuracy of gas source localization degrades with lower measurement densities, emphasizing the importance of careful parameter tuning. Additionally, the influence of obstacles on the algorithm's performance was found to be minimal, with the primary performance drivers being the density and spatial distribution of the measurements.

Comparisons with the Kernel DMV method highlighted GBP's superior ability to reconstruct gas plumes under sparse data conditions. However, GBP requires significantly more computational resources, posing challenges for real-time applications. Future work should explore further hyperparameter tuning, real-time integration, and additional sensor modalities (such as wind measurements) to further evaluate the method and compare it against state-of-the-art methods in order to enhance localization accuracy and efficiency.

[1] *L. C. Rhodes, C. and W.-H. Chen, "Structurally aware 3d gas distribution mapping using belief propagation: A real-time algorithm for robotic deployment", 2022*