WS 2025-2026, SMT-ROB, DISAL-SP206 Project Summary

Gas Detection with Thermal Cameras

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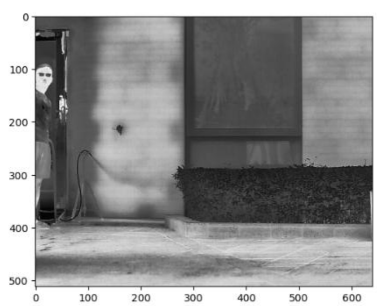
Industrial gas leaks represent a major safety and environmental risk due to their potential toxicity, flammability and human health. Traditional in-situ gas sensors, while accurate, suffer from limited spatial coverage and sensitivity to environmental conditions. This project investigates the use of thermal imaging for non-contact gas leak detection, with a particular focus on uncooled thermal camera as they are better suited to be attached to a drone.

The objective of this work was to design, implement, and evaluate gas detection algorithms on thermal imagery, and to compare the performance of classical methods against deep learning–based approaches. The experiments were conducted primarily on the GAS-DB dataset, acquired with a cooled thermal camera, which served as the main evaluation benchmark. Additional public datasets were used for pre-training and domain adaptation experiments. It is important to note that no dataset acquired with uncooled thermal cameras was used in this study.



First, a classical image processing pipeline was developed. This approach provided an interpretable baseline and demonstrated high performance under controlled conditions with consistent backgrounds. However, when evaluated on the full dataset with varying scenes, its performance degraded significantly. This highlighted the limited robustness and poor generalization capability of handcrafted feature-based methods in real-word environments.

In addition to the classical appearance-based pipeline, a motion-based gas detection approach was explored as a complementary method. This approach illustrates how temporal information can be exploited for gas plume detection in image sequences. Based on dense optical flow, it highlights slow and diffuse motion patterns characteristic of gas plumes. While effective under controlled conditions with stable camera viewpoints, the method could remain sensitive to camera motion and environmental disturbances.

In parallel, a deep learning approach based on the YOLOv8s object detection model was implemented. The model achieved a higher performance across diverse backgrounds. Additional experiments revealed that the model relied on visible gas source, which reduces the model's performance when removed. Transfer learning and domain adaptation experiments using grayscale and inverted RGB datasets were conducted to improve model's performance in absence of big dataset.

	Classical (1 background)	Classical (all dataset)	Deep learning
Precision	0.86	0.87	0.71
Recall	0.75	0.3	0.62
F1-score	0.81	0.45	0.66

Table 1 Results across methods

In conclusion, this project demonstrates that deep learning approaches outperform classical methods for thermal gas leak detection, particularly in heterogeneous environments. While handcrafted techniques remain useful for small and controlled datasets, learning-based methods provide superior robustness. The results also underline the importance of dataset quality and domain-specific training in the design of gas detection systems.

As future work, this methodology should be transferred and evaluated on datasets acquired with uncooled LWIR cameras in order to assess its practical applicability for lightweight, low-cost, and drone-deployable gas monitoring systems. This step will be crucial to determine whether the performance achieved on cooled thermal imagery can be maintained under more realistic operational constraints.