Gas Source Location Classification in Built Environment with a Sensor Network

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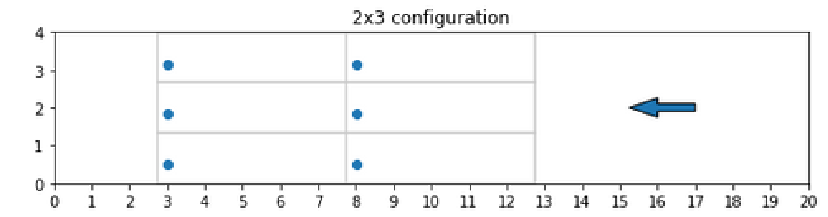
Introduction

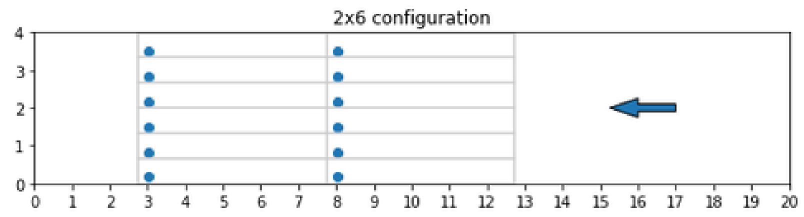
Gas Source Localization (GSL) is the process of identifying the source of a gas release in an environment, which is vital for environmental safety, industrial security, and emergency response. GSL is becoming increasingly important as industries expand, leading to a higher risk of gas releases, whether accidental or deliberate. In situations where gas leaks pose a danger to humans, autonomous methods like using sensor networks or mobile robots become valuable for locating the source without risking human lives.

In this project, GSL is approached as a classification challenge, with the goal of identifying the region of the gas source using stationary sensors. What distinguishes this approach is its exploration of the fusion of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models. This combination leverages the spatial and temporal characteristics of the problem with the aim of accurately locating gas sources in various environments.

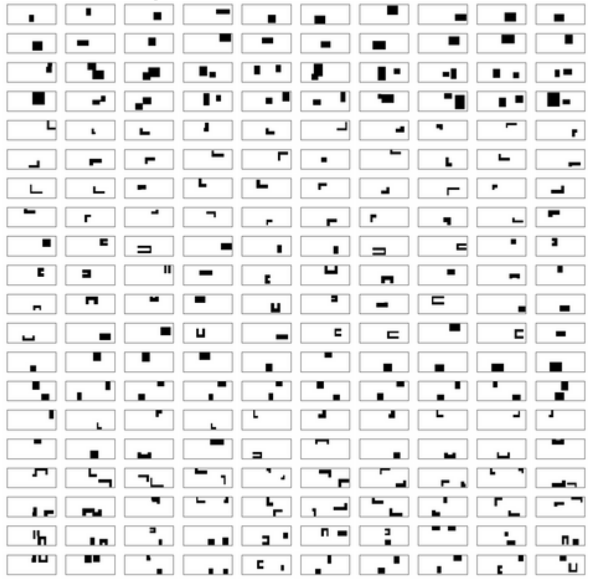
Experimental environment

The challenge involves accurately classifying the source position into specific regions using sensor measurements and environmental information, with consideration for top-k accuracy. Factors like sensor quantity, distribution, region count, spatial division method, and k value are crucial variables affecting problem complexity. The experimental setup utilizes a virtual wind tunnel environment to simulate airflow patterns and controlled gas emissions, enabling sensor data collection through dispersion modeling.

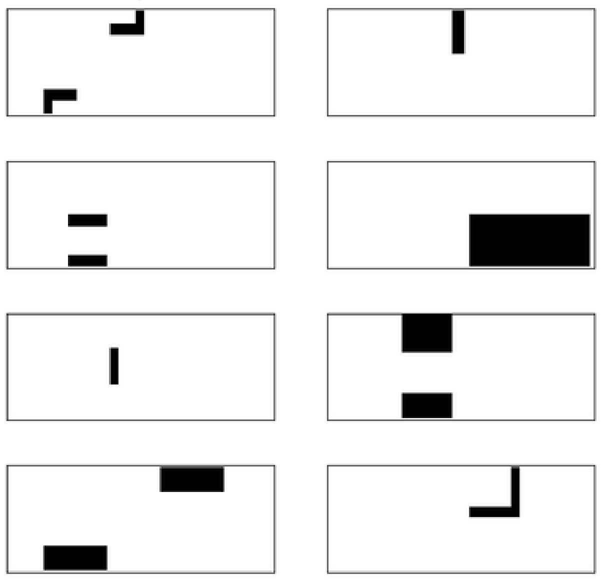




Training maps



Testing maps

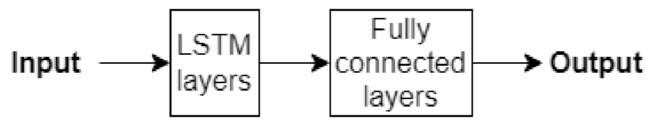


Methods

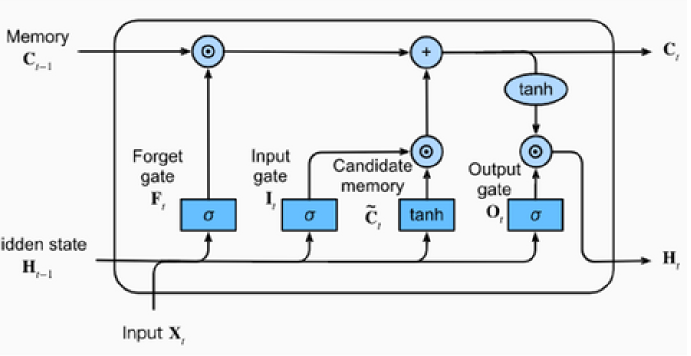
LSTM

The LSTM network takes sensor data as input, including key measurements like gas concentration, wind speed, and wind angle.

To enhance data preprocessing, we aggregate 15 consecutive measurements to create one time frame. We then calculate the mean value for each group of measurements, resulting in 10 time frames per sample.



LSTM diagram



Credits:
https://d2l.ai/chapter_recurrent-modern/lstm.html
Yildirim, Melih & Kaçar, Firat. (2019). Adapting Laplacian based filtering in digital image processing to a retina-inspired analog image processing circuit. Analog Integrated Circuits and Signal Processing

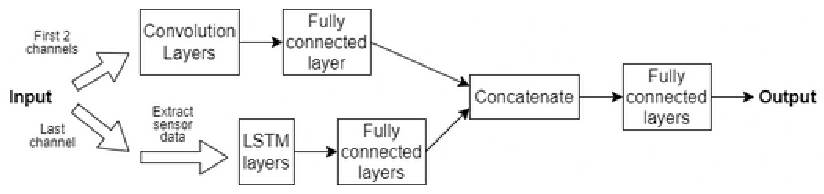
First hybrid network

Similar to the LSTM network, we perform similar preprocessing for sensor data, which occurs before integrating it with map data. In this setup, the input is a 64×64 image with 3 channels:

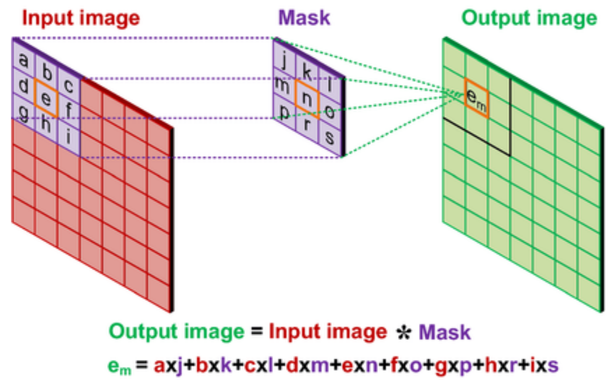
- The first channel encodes obstacle information in binary form.
- The second channel relates to the signed distance function.

Both of these channels go through processing using CNN layers to extract spatial features.

- Then, the last channel contains sensor data.



Convolution diagram

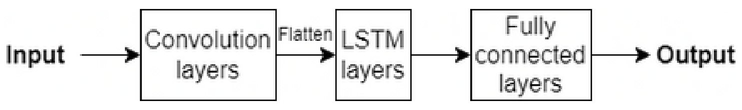


Second hybrid network

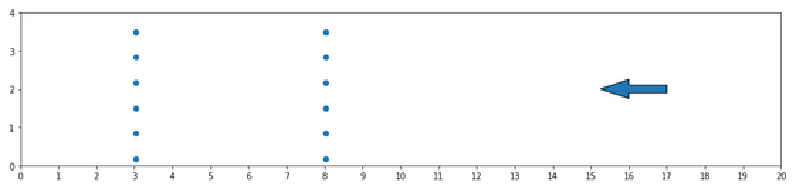
In the second hybrid network, we apply the same preprocessing as in previous configurations before combining inputs. We integrate sensor and map data as follows:

- **First channel:** Binary obstacle information.
- **Second channel:** Signed distance function.
- **Subsequent channels:** Sensor measurements for specific features over time, mapped to the image grid. Missing data is represented as 0. This results in 30 additional channels, organized by feature and time step.

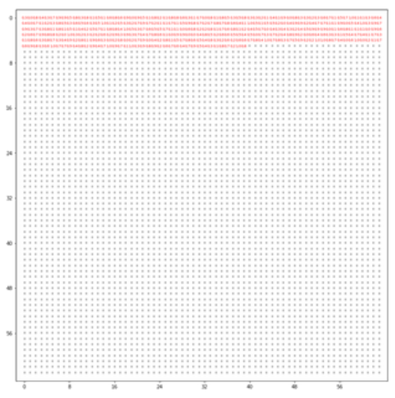
All channels pass through convolution layers, creating a 32-channel image input (2 for map, 30 for data). The output is a 30-channel image representing data for ten time frames and three features.



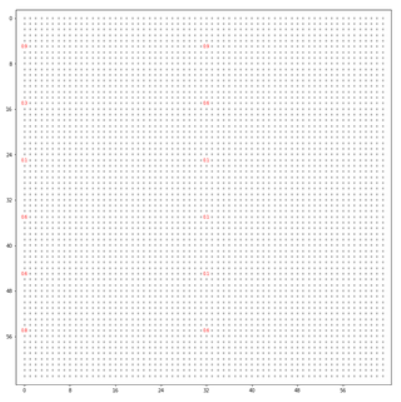
Example sensor configuration



Example of third channel of the input to the first hybrid network



Example one of the last 30 channels of the input to the second hybrid network



Results

	Obstacle-free environment 2x3 configuration		Obstacle-free environment 2x6 configuration		Built environment 2x3 configuration		Built environment 2x6 configuration	
	Accuracy	Top-2 accuracy	Accuracy	Top-2 accuracy	Accuracy	Top-2 accuracy	Accuracy	Top-2 accuracy
LSTM	84.30%	91.92%	93.45%	99.98%	51.56%	70.62%	53.44%	74.69%
First hybrid network	82.95%	89.55%	93.17%	99.95%	52.19%	72.81%	54.06%	75.00%
Second hybrid Network	90.05%	97.88%	96.50%	99.98%	64.38%	85.62%	55.00%	72.50%

Conclusion

The study focused on Gas Source Localization (GSL) using static sensors to approximate the source's position. The approach treated GSL as a classification challenge, dividing the space into regions to identify the gas source's location. Unlike previous work, this study allowed for multiple viable source locations within each region and aimed for versatility across different environments.

Two hybrid architectures combining Convolutional Neural Networks (CNN) and LSTM as well as a standard LSTM network were tested in a virtual wind tunnel environment, yielding promising results. While not groundbreaking, these outcomes provide a solid foundation for future research and improvements in GSL, with the goal of creating safer and more secure environments.

References

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Acknowledgments

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