Methane plumes detection on hyperspectral images with a matched filter variant and deep learning

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Introduction

Methane is a gas for which the greenhouse effect is 80 times more important (over 20 years) than for $CO2$ [1].
We could control a large part of methane emissions because they are coming from oil and gas infrastructure.

To detect those emissions, we use data from the satellite PRISMA. It is a satellite which provides hyperspectral images (HSI) with data on wavelengths useful for detecting methane.

1. In Intergovernmental Panel on Climate Change, editor,Climate Change 2013 - The Physical Science Basis, pages 659–740. Cambridge University Press, Cambridge, 2013.

Data presentation

PRISMA provides HSI in the infrared spectrum. Those images contain the 1600-1800nm and the 2300-2400nm wavelength range, where are located methane absorption features.

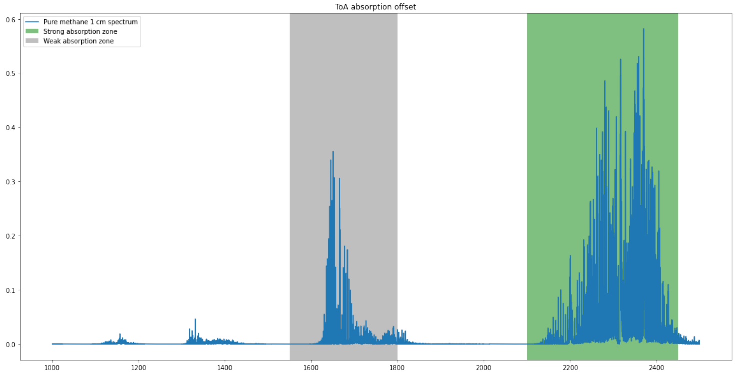

Figure – Methane absorption spectrum .

The Matched Filter

The matched filter [2] (MF) is one of the most popular method for plume detection on HSI. The matched filter is based on two assumptions :

- The background is following a gaussian distribution $\mathcal{N}(\mu, \Sigma)$
- The CH4 mixing ratio of the plume is weak compared to the mixing ratio of the atmosphere.

This last assumption allow us to obtain an additive anomaly model where an observation with a plume can be written as :

$$\text{plume} = \text{background} + \alpha t \tag{1}$$

The vector t represents the direction of the expected perturbation when observing a plume. In our case :

$$t = -K_{\text{CH4}}\mu, \tag{2}$$

where K_{CH4} is the diagonal matrix whose coefficients are the ones of the methane absorption spectrum.

2. Guanter et al (2021), Mapping methane point emissions with the PRISMA spaceborne imaging spectrometer, Remote Sensing of Environment

The Matched Filter

The MF detector is defined by :

$$\mathcal{D}_{MF}(x) = \frac{t^T \Sigma^{-1}(x - \mu)}{t^T \Sigma^{-1} t}, \tag{3}$$

where μ and Σ are the mean and covariance of the background, and t is the target vector.

The matched filter returns the excess methane mixing ratio of the observation.

Matched filter

First results

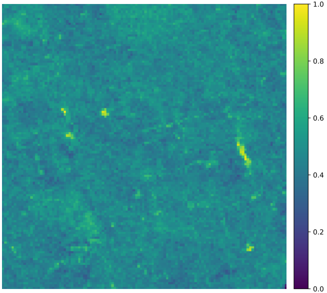

Figure – Matched filter result (Date : 2020/09/25)

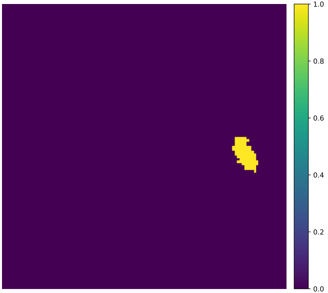

Figure – Ground truth.

Adjusted spectral matched filter

A major drawback of the matched filter is that we can detect anomalies that are not in the direction of the target vector if there are outliers.

To avoid false positives, we need to penalize the score of these outliers. This is done by using the squared of the Manalahobis distance, also known as the Reed-Xiaoli score (RX) :

$$\mathcal{D}_{RX}(x) = (x - \mu)^T \Sigma^{-1} (x - \mu) \tag{4}$$

This leads to the adjusted spectral matched filter (ASMF) [3].

$$\mathcal{D}_{ASMF}(x) = \mathcal{D}_{MF}(x) \cdot \left(\frac{\mathcal{D}_{MF}(x)}{\mathcal{D}_{RX}(x)} \right)^n . \tag{5}$$

In practice we use $n = 2$.
The ASMF significantly reduces the number of false positives. However, it can lower the detection score of actual plumes because plumes can also have a high RX score.

3. Gao Let al. (2015), Adjusted spectral matched filter for target detection in hyperspectral imagery, Remote Sensing

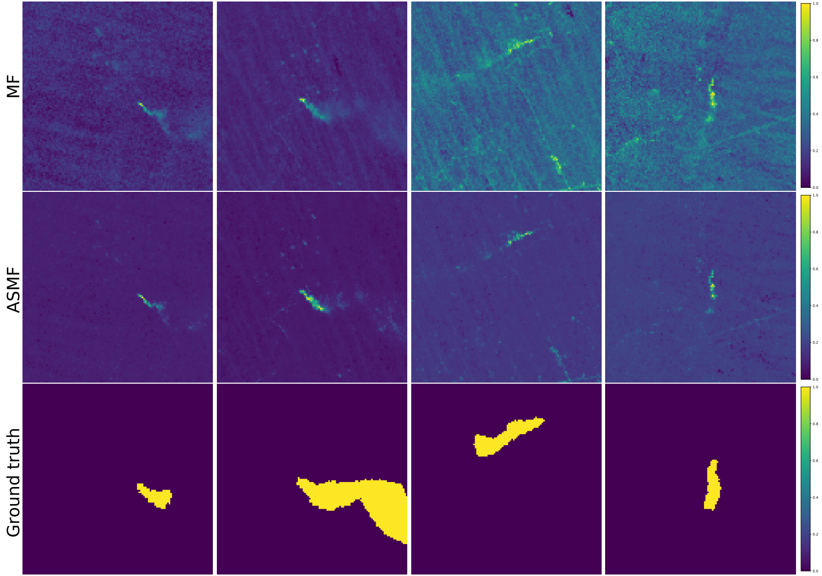

Figure – Comparison between the Matched Filter and the ASMF on four different plumes. The ground truth includes the entire plume, including parts with low methane concentration and therefore not very visible on the MF or ASMF.

Deep neural network approach

We want to complete the ASMF with a deep learning approach. The aim of a DCNN would be to detect based on their shape.

We use a standard U-net architecture to perform the segmentation of the plumes. The input of the network is not the PRISMA radiance image or the ASMF but the standard MF image. This choice is motivated by two reasons :

- the original PRISMA images are very large spatially and spectrally, which makes the training of a network very long
- Unlike the ASMF, the MF provides a proxy for the true methane concentration. In the ASMF, usually only the source is visible and the rest of the plume is not detectable. Therefore, we have to use the MF to detect the plume shapes.

Neural network training

Due to the small number of PRISMA images available with plumes, DCNN training is based on simulations.
We simulate plumes in MF images of plumes by using a datasets of plumes from other satellites.

We compute the MF on PRISMA images without plumes then we add at a random location a random plume from the dataset. The plume is simulated with the same shape and concentration in CH4 as in the original dataset.

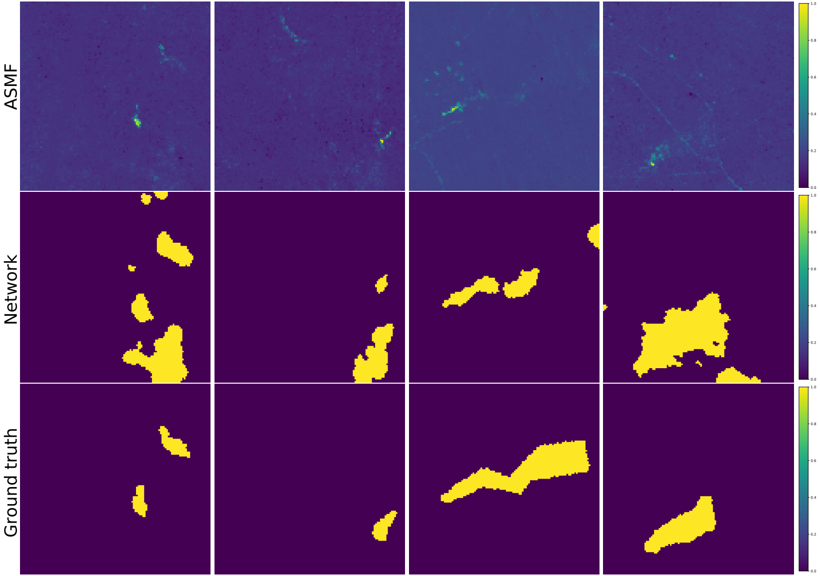

Figure – Comparison between the ASMF and the DCNN on four different plumes.

Numerical results

The detection thresholds are set up to maximize the F1 score.

	Recall	Precision	F1
MF	0.53	0.22	0.31
Network	**0.88**	0.42	0.57
ASMF	0.84	0.60	0.70
ASMF+network	0.62	**0.83**	**0.71**

Table – Numerical results using actual PRISMA plumes