Artificial Intelligence for Methane Mitigation : Through an Automated Determination of Oil and Gas Methane Emissions Profiles

Jade E. Guisiano
ISEP
École Polytechnique
UN Environment Programme
Paris, France
`jade-guisiano@outlook.fr`

Éric Moulines
École Polytechnique
Palaiseau, France

Thomas Lauvaux
Université de Reims Champagne Ardenne
Reims, France

Jérémie Sublime
ISEP
Paris, France

Abstract

The oil and gas sector is the second largest anthropogenic emitter of methane, which is responsible for approximately 25% of global warming since pre-industrial times [1]. In order to mitigate methane atmospheric emissions from oil and gas industry, the potential emitting infrastructure must be monitored. Initiatives such as the Methane Alert and Response System (MARS), launched by the United Nations Environment Program, aim to locate significant emissions events, alert relevant stakeholders, as well as monitor and track progress in mitigation efforts. To achieve this goal, an automated solution is needed for consistent monitoring across multiple oil and gas basins around the world. Most methane emissions analysis studies propose post-emission analysis. The works and future guidelines presented in this paper aim to provide an automated collection of informed methane emissions by oil and gas site and infrastructure which are necessary to dress emission profile in near real time. This proposed framework also permits to create action margins to reduce methane emissions by passing from post methane emissions analysis to forecasting methods.

1 Introduction

Atmospheric methane accounts for about a quarter of global warming since pre-industrial times, and the oil and gas sector is the second largest anthropogenic source of methane. To meet the mitigation targets set out in the Global Methane Commitment, governments need to implement effective mitigation measures at the scale and pace required. Current regulations are based on national methane emissions inventories, which studies show significantly underestimate methane sources in all emissions sectors. Most of the discrepancy in emissions estimates is due to the failure to include super-emitters in emissions inventories. Such sources are characterized by high emission rates and account for 40% of total methane emissions on average. Emission estimates can be greatly improved by taking advantage of the increasing availability of methane emission data. This can be achieved by using and combining data from high-resolution satellites to measure methane concentrations, which has the advantage of being the more cost-effective tool for monitoring methane emissions. The International Methane Emissions Observatory (IMEO), launched by the United Nations Environment Program, is

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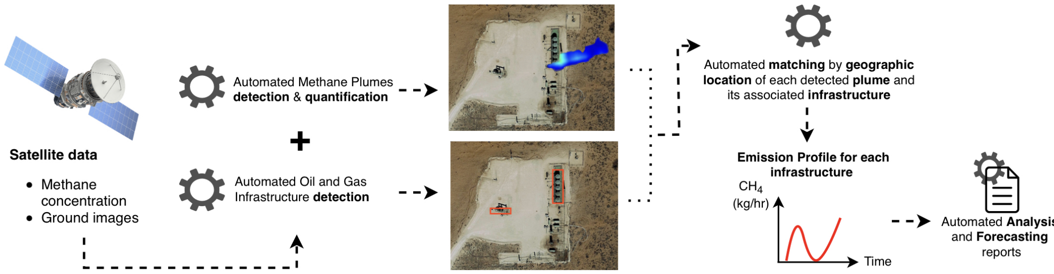

Figure 1: **Emissions profile determination process.** *Satellite images @Google Earth*

an initiative that aims to create a global public dataset of empirically verified methane emissions by integrating and combining data primarily from many sources, including various point-source satellite data sources. However, once these methane emissions are identified and quantified globally, they must be traceable to the levels of the O&G supply chain, site, operator, and infrastructure at which they originated in order to understand their origins and thus better tailor regulations and mitigation actions. The Methane Alert and Response System (MARS), launched by the UN environmental program at COP27, aims to notify relevant governments and companies of major emissions events in or near their jurisdictions or operations, which could help stop unwanted methane leaks more quickly. To monitor methane emissions in various O&G basins around the world, this task must be automated using machine learning algorithms.

Indeed, as illustrated on the Figure 1, artificial intelligence could play a critical role at several stages of the worldwide methane emissions monitoring process by permitting a nearly continuous monitoring in near real time. Various studies [2, 3, 4, 5, 6, 7] using deep learning algorithms propose to automatically detect and quantify methane plumes from multispectral and hyperspectral satellite data. Other studies have examined O&G site type detection[8, 9] and infrastructure detection[10]. These two main steps should enable the generation of geographical coordinates for both methane plumes and their corresponding infrastructures. An automatic matching process is also required to associate all the plumes detected with the emitting infrastructures. Over a medium-to-long-term period, all these steps should make it possible to obtain time series of methane emission levels by infrastructure, site, operator, region and country. Obtaining such data over the long term will make it possible to characterize and predict emissions behavior. In this paper, focus will be given to the detection of infrastructure and the matching between infrastructures and methane plumes.

2 Oil and Gas infrastructure automated detection

Sites in the oil and gas industry that contain wells, storage tanks, or compressor infrastructures are considered to be significant contributors of fugitive emissions and therefore form the targets that we wish to automatically detect. Existing approaches [11, 12, 13, 14, 15, 16, 10, 17, 18] to oil and gas infrastructure detection typically do not allow for the simultaneous detection of multiple infrastructures. One of our recent study[19] enabling automatic detection of compressors, tanks, and well infrastructures simultaneously and compare different supervised object detection algorithms.

Database A database (OG)[1] of various high-resolution aerial images from 15 cm to 1 m per pixel (Google Earth) of O&G infrastructures was developed specifically for these tests and contains for each image the labelled bounding box of the respective infrastructure (930 images, 1951 objects). These images were extracted from the Permian Basin, the largest oil and gas basin in the world, where the distance between sites is very small (so that a maximum of infrastructures can be captured within a reduced number of images).

For these tests, 3 categories of object detection algorithms were used: single-stage detector (YOLO)[20], two-stage detector (FASTER-RCNN)[21] and transformer-based algorithm (DETR)[22]. Each of these algorithms was pre-trained on the COCO dataset [23] (consisting of a large set of annotated common objects) and fine-tuned on the OG database.

[1] `https://universe.roboflow.com/thesis-ffaad/og-otgc5`

Figure 2: Detection results of YOLO, FASTER-RCNN, DETR on 4 different images. Source: @Google Earth

Results tend to show a better general performance for the YOLO model, with an average accuracy of over 90% (comparisons of algorithms detection illustrated in Figure 2 compare to 85,5% for DETR and 48,8 for FASTER-RCNN. Through our tests, YOLO confirms its general ability to detect and recognize O&G infrastructures with a quite high reliability. However, certain parameters remain to be determined:

1. The limit of spatial resolution that allows these algorithms to detect infrastructures;
2. The replicability of these algorithms in other O&G basin with non-similar infrastructures.

Point (1) would make clear which satellite data can be used to apply these algorithms by testing our train model on images with different categories of spatial resolution. As for point (2), replicability can be tested using transfer learning from pre-trained Permian models applied to new basins. Otherwise, these models would have to be re-trained on images from each basin. However, the task of extracting and labeling a sufficient set of images/objects is time consuming, so a possible solution could be to test few-shot and self-supervised learning algorithm which requires only few training images.

3 Automated matching between methane plumes and infrastructures

In one of our studies[24], we focused on using data from the open-source PermianMAP project[2], which provides access to a list of detected plumes associated with their geographic coordinates in O&G sites (identified by their position in the supply chain) and the concerned operator for each of these sites in the Permian Basin (USA). These data enabled the development of O&GProfile, the first automated method to link all methane plumes detected from high resolution satellite to sites parts of oil and gas supply chain (extraction, processing and production) and the respective operator. As illustrated on the Figure 3, O&GProfile is based on the use of unsupervised machine learning methods for clustering purposes (DBSCAN)[25] and a semi-automatic correction method. This is the first method that allows methane detection to be automatically associated with the type of site and operator causing the methane leakage. These mappings allow for emission profiling by site and operator by combining point satellite and PermianMAP tagged detections.

Results O&GProfile is able to correctly assign satellite locations of point sources 98.8% of the time, and the semi-automatic correction process allows to achieve 100% of correct assignments.

[2] `https://www.permianmap.org`

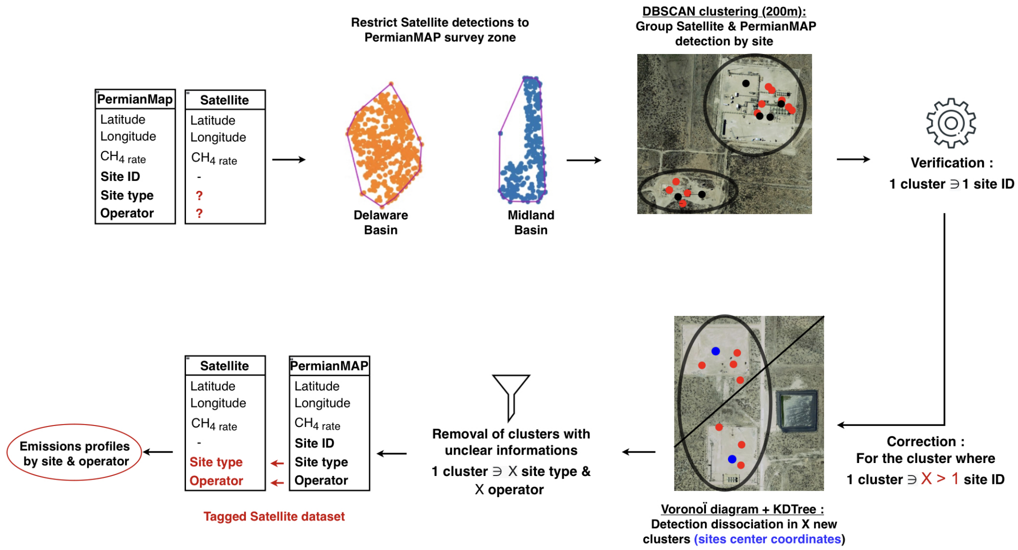

Figure 3: **O&G Profile method:** Automated assignment of detected methane plume to O&G sites type and operators using DBSCAN and semi-automatic correction method

O&GProfile may prove useful to continue monitoring methane emissions at specific sites that were covered in previous ground survey, allowing surveys to continue over time. However, this method is completely dependent on previous studies and therefore cannot be applied in regions where survey and measurement data do not exist.

4 Perspectives

Infrastructure detection: coordinates extraction The previous as shown that current state of the art object detection algorithms are able to recognize with a quite high confidence oil and gas infrastructure. However, the previous test were conducted on images which do not permit to access and collect the geographic coordinates of each detected infrastructures (which are needed to be matched with methane plumes). By adapting object detection algorithm to satellite data (Mainly by keeping the geographic coordinate data of each pixel) scans of the O&G basins in the world could permits to obtain a list of infrastructures, each with its type and bounding box coordinates.

Plumes and infrastructures coordinates matching Once the list of infrastructures and plumes with their locations is established, an unsupervised spatial clustering method similar to that used for O&GProfile could be used to connect the plumes to the nearest infrastructure (assumed to be their origin). It should be noted, however, that there is some uncertainty in determining the origin of an exhaust plume (generally quantified by inversion models), which should be considered when assigning it to the nearest infrastructure.

Profiling and Forecasting By associating the detected plumes (with the amount of methane emissions) with the infrastructures, we can obtain a time series of methane emissions for each infrastructure. Acquiring a sufficiently long time series will allow us to capture the emission behavior of each infrastructure and thus establish its emission profile. Access to such a time series should allow us to move from analyzing emissions after the fact to predicting them, which could prevent many methane leakages, for example, with tendency analysis for methane leaks forecasting and also spatio-temporal forecasting of methane super emitters.

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