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3D-CNN and Autoencoder-Based Gas Detection in Hyperspectral Images

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Abstract: The detection of gas emission levels is a crucial problem for ecology and human health. Hyperspectral image analysis offers many advantages over traditional gas detection systems with its detection capability from safe distances. Observing that the existing hyperspectral gas detection methods in the thermal range neglect the fact that the captured radiance in the longwave infrared (LWIR) spectrum is better modeled as a mixture of the radiance of background and target gases, we propose a deep learning-based hyperspectral gas detection method in this article, which combines unmixing and classification. The proposed method first converts the radiance data to luminance-temperature data. Then, a 3-D convolutional neural network (CNN) and autoencoder-based network, which is specially designed for unmixing, is applied to the resulting data to acquire abundances and endmembers for each pixel. Finally, the detection is achieved by a three-layer fully connected network to detect the target gases at each pixel based on the extracted endmember spectra and abundance values. The superior performance of the proposed method with respect to the conventionalhyperspectral gas detection methods using spectral angle mapper and adaptive cosine estimator is verified with LWIR hyperspectral images including methane and sulfur dioxide gases. In addition, the ablation study with respect to different combinations of the proposed structure including direct classification and unmixing methods has revealed the contribution of the proposed system.

Keywords: *Gas emission detection, Deep Learning, Hyperspectral image analysis, Longwave infrared (LWIR) spectrum ,Hyperspectral gas detection, Radiance data, Luminance-temperature data, Classification.*

1.INTRODUCTION

Imaging spectroscopy has been utilized by physicists and chemists for overthirty years to identify materials and their compositions. The idea of hyperspectralremote sensing began in the mid-1980s and is still used by geologists to map minerals. The ability to detect materials depends on several factors, including the spectrometer'sspectral range and resolution, the material's abundance, and its absorption properties. In recent years, gas leaks have become a significant environmental issue indeveloped countries. Some harmful gases contribute to global warming and poseshort-term risks like explosions and long-term health risks, such as cancer, to nearbyresidents and workers. To reduce these risks, environmental authorities must monitorchemical and industrial plants for gas emissions. Infrared remote sensing technologydistance.

To implement this technology, forward-looking infrared and Hyperspectral Cameras are used in high-risk areas for gas detection. These camerascan captureimages across different wavelengths and work in medium-wave infrared (3–5 μm) andlong-wave infrared (7–14 μm) bands. They have been employed to detect variousgases, including carbon dioxide, propane, methane, and ammonia, among others. Detection methods typically use statistical detection techniques combined with basicsignal processing operations like data transformation and matched filtering. Pioneer studies in gas detection include work by Pogorzala, who used linearregression on synthetic images to detect ammonia and Freon-114. Vallières et al. developed a method that converts hyperspectral data to temperature data, removesbackground data, and applies spectral matched filtering to identify gas-containingpixels. In another approach, Spisz et al. utilized principal component analysis forbackground removal before applying detection techniques.The other studies have focused on automatic detection of waste gases, employingmethods that filter possible areas based on critical wavelengths, followed by matchedfiltering. Hirsch and Agassi presented a method for gas detection that does not rely onbackground information, using K-Means segmentation and correlation analysis. Kastek and Piątkowski proposed a method to identify gases in turbulent fumes using aspectral angle mapper. Additionally, studies by Kuflik and Rotman have explored theminimum number of bands required for gas detection.

2. LITERATURE SURVEY

R. O. Green et al., 1998.[1] Imaging spectroscopy is of growing interest as a new approach to Earth remotesensing. The Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) was thefirst imaging sensor to measure the solar reflected spectrum from 400 nm to 2500nm at 10 nm intervals. The calibration accuracy and signal-to-noise of AVIRISremain unique. The AVIRIS system as well as the science research andapplications have evolved significantly in recent years. The initial design andupgraded characteristics of the AVIRIS system are described in terms of the sensor, calibration, data system, and flight operation. This update on the characteristics ofAVIRIS provides the context for the science research and applications that useAVIRIS data acquired in the past several years. Recent science research andapplications are reviewed spanning investigations of atmospheric correction, ecology and vegetation, geology and soils, inland and coastal waters, theatmosphere, snow and ice hydrology, biomass burning, environmental hazards, satellite simulation and calibration, commercial applications, spectral algorithms, human infrastructure, as well as spectral modelling.

Govender, K. Chetty and H. Bulcock, 2007.[2] Multispectral imagery has been used as the data source for water and landobservational remote sensing from airborne and satellite systems since the early1960s. Over the past two decades, advances in sensor technology have made itpossible for the collection of several hundred spectral bands. This is commonlyreferred to as hyperspectral imagery. This review details the differences betweenmultispectral and hyperspectral data; spatial and spectral resolutions and focuseson the application of hyperspectral imagery in water resource studies and, inparticular the classification and mapping of land uses and vegetation.

P. Y. Foucher and S. Doz, 2023,[3] Whether for environmental or industrial applications, infrared hyperspectraltechnology is an efficient tool for studying and monitoring gas leaks. But nowusers need to access to real-time gas leak quantification mapping. In this purpose, several gas tests campaign has been conducted since 2015 in order to validate ouralgorithms for visualizing and quantifying gas plumes for different kind of gas in avery large range of flow rate (0.5 g/s up to 250g/s) from hyperspectral infraredcameras in particular using TELOPS technology. In this paper, we present recentresults from real time ground and airborne quantification during differenthyperspectral campaigns. In particular during the NAOMI project in collaborationwith TOTAL, hundreds of controlled methane leakages tests have been fulfilled. The real time algorithm IMGSPEC developed by ONERA shows a real goodagreement with ground truth in term of gas flow rate. Then, airborne campaignresults show the developed quantification algorithm coupling with airborne TelopsHyper-Cam system (from 600m to 1500m) provides real-time quantitative map(ppm.m), estimation of local concentration (ppm) and leakage flow rate withassociated uncertainties. We finally show IMGSPEC application to other kind ofgas as Acetone or Methanol.

A. Vallières et al., 2005.[4] Standoff detection, identification and quantification of chemicals in the gaseousstate are fundamental needs in several fields of applications. Sensor requirementsderived from these applications include high sensitivity, low false alarms and real-time operation, all in a compact and robust package suitable for field use. Thethermal infrared portion of the electromagnetic spectrum has been utilized toimplement such chemical sensors, either with spectrometers (with no or moderateimaging capability) or with imagers (with moderate spectral capability). Only withthe recent emergence of high-speed, large format infrared imaging arrays has itbeen possible to design chemical sensors offering uncompromising performance inthe spectral, spatial, as well as the temporal domain. It is clear from analyticalstudies that the combined spatial and spectral information holds enormouspromises on improving the current performance of passive detection, identification and quantification of chemical agents. This paper presents detection, identificationand quantification algorithms developed for hyperspectral imagers operating in thethermal infrared. The effectiveness of these algorithms is illustrated using gaseousreleases datacubes acquired using the Telops FIRST imaging spectrometer in thefield.

G. Fortin, F. Bouffard, H, P. Lacasse and J. Lévesque, 2013.[5] Imaging Fourier-transform infrared (FTIR) spectroscopy is a powerful method forthe passive remote detection and identification of vapor emanations and surfacecontaminations. In the Defense and Security context, imaging FTIR can be used forthe remote surveillance of locations suspected of illicit product fabrications. DRDCValcartier recently initiated the development and field-validation of the novelimaging FTIR sensor MoDDIFS (Multi-option Differential Detection and ImagingFourier Spectrometer) to address this remote sensing application. The proposedsystem combines the clutter suppression efficiency of the differential detectionapproach with the high spatial resolution provided by the hyperspectral imagingapproach. The MoDDIFS sensor includes two configuration options, one forremote gas detection, and the other for polarization sensing of surfacecontamination. This paper reviews recent results obtained with MoDDIFS for thepassive standoff detection of gases and liquid contaminants. Hyperspectralmeasurements done on difluoroethane, diethyl ether (gases) and SF96 (liquid)serve to develop, test and validate GLRT-type detection algorithms. Detectionresults are presented and discussed in terms of the GLRT detection attributes.

A. W. Messinger, 2004.[6] Recently, interest in gaseous effluent detection, identification, and quantificationhas increased for both commercial and government applications. However, theproblem of gas detection is significantly different than the problems associatedwith the detection of hard-targets in the reflective spectral regime. In particular, gassignatures can be observed in either emission or absorption, are both temperatureand concentration dependent, and are viewed in addition to the mixed backgroundpixel signature from the ground. This work applies standard hard-target detection schemes to thermal hyperspectral synthetic imagery. The methods considered hereare Principal Components Analysis, Projection Pursuit, and a Spectral MatchedFilter. These methods will be compared both quantitatively and qualitatively withrespect to their applicability to the gas detection problem. Comparison to truthoutputs from the synthetic data provides an accurate quantitative measure of thealgorithmic performance. Principle Components and Projection Pursuit are shownto have similar performance, and both are better than the Spectral Matched Filter. Additionally, both Principal Components and Projection Pursuit demonstrate theability to separate regions of absorption and emission in the plume.

T. Piatkowski, R. Dulski, M. Chamberland, P. Lagueux and V. Farley,2012[7] This paper presents detection and identification of gases using an infrared imagingFourier-transform spectrometer. The principle of operation of the spectrometer andthe method for gases detection and identification has been shown in the paper. Thevariation of a signal reaching the IFTS caused by the presence of a gas has beencalculated and compared with the reference signal obtained without the presence ofa gas in IFTS's field of view. Some result of the detection of various types of gaseshas been presented too.

F. Omruuzun and Y. Y. Cetin,2015.[8] Segmentation and identification of compounds or materials existing in a scene is acrucial process. Hyperspectral sensors operating in different regions of theelectromagnetic spectrum are able to quantify spectral characteristics of materialsin different states. Due to the fact that some chemical compounds in gas state haveinsignificant light reflectance characteristics in visible region of the spectrum, imaging sensors operating in infrared regions are needed to sense energyabsorbency characteristics of these compositions. The present study proposes anovel method for detection of flammable gases in long-wave infrared hyperspectralimages. Proposed method begins with Black-Body radiation curve compensation. Since a priori information regarding the compounds in the scene is not alwaysavailable, endmember spectral signatures are extracted with VCA hyperspectralunmixing algorithm.

3. PROPOSED METHODOLOGY

This proposed methodology focuses on improving the accuracy and efficiency of gas detection in hyperspectral images using a 3D Convolutional Neural Network (3D CNN) and an Autoencoder-based approach. The primary goal of the proposed model is to enhance feature extraction and classification capabilities, ensuring precise identification of gases in hyperspectral data. It employs a deep learning-based framework that integrates techniques from computer vision, spectral image processing, and deep neural networks to achieve its objectives.Overall, this research is designed to address the challenges associated with hyperspectral gas detection by applying advanced deep learning techniques. The combination of 3D CNNs and Autoencoders enhances feature representation, improves detection accuracy, and provides reliable results.It finds applications in various fields, including environmental monitoring, industrial safety, and remote sensing, where accurate gas identification in hyperspectral images is critical for analysis and decision-making.

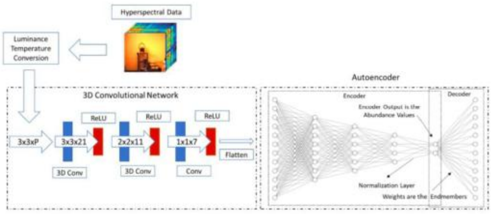


Figure 1: Proposed 3D-CNN system.

The proposed methodology typically includes the following key components:

Hyperspectral Data Preprocessing: The process begins with preprocessing hyperspectral images to remove noise, correct distortions, and normalize spectral data. This step ensures that the input data is clean and suitable for further processing.

Feature Extraction Using 3D CNN: A 3D Convolutional Neural Network (3D CNN) is employed to extract spatial and spectral features from hyperspectral images. This approach effectively captures the spatial dependencies and spectral correlations necessary for accurate gas detection.

Dimensionality Reduction with Autoencoder: An Autoencoder-based approach is used to reduce the dimensionality of the hyperspectral data while preserving essential features. This step helps improve computational efficiency and enhances feature representation for better classification accuracy.

Gas Classification and Detection: The extracted features are passed through a classification model that identifies the presence of specific gases in hyperspectral images. The deep learning framework enhances detection accuracy by learning complex patterns within the hyperspectral data.

Performance Metrics Evaluation: To assess the model's effectiveness, various performance metrics such as Accuracy, Precision, Recall, F1-score, and RMSE (Root Mean Squared Error) are computed. These metrics measure the reliability of gas detection and classification.

Customization and Parameter Tuning: The methodology allows for parameter adjustments such as the number of CNN layers, activation functions, learning rate, and loss function selection to optimize model performance for different hyperspectral datasets.

Output: The primary output of this model is a segmented hyperspectral image with detected gas regions accurately marked. The model provides enhanced visibility and classification of gas emissions. Evaluation and Benchmarking: The proposed method is evaluated against benchmark hyperspectral datasets, comparing its accuracy and efficiency with existing gas detection techniques. The goal is to achieve superior or comparable performance to state-of-the-art methods in hyperspectral gas detection.

Applications:

The enhanced gas detection in hyperspectral images using 3D CNN and Autoencoder can be applied in various fields, including**:**

- Environmental monitoring (detecting and analysing air pollution and greenhouse gas emissions).
- Industrial safety (identifying hazardous gas leaks in factories and chemical plants).
- Agriculture (monitoring methane and ammonia levels to improve crop management).
- Remote sensing (analysing atmospheric gases).

Advantages:

3D CNN and Autoencoder-based gas detection in hyperspectral images utilize deep learning and feature extraction techniques to enhance detection accuracy and efficiency. The key advantages include:

- High Detection Accuracy: 3D CNN effectively captures spatial-spectral features, leading to improved accuracy in identifying and classifying gases in hyperspectral images.
- Feature Extraction Efficiency: Autoencoders reduce the dimensionality of hyperspectral data while preserving essential features, making the detection process more efficient.
- Improved Noise Reduction: The deep learning architecture helps suppress noise and irrelevant spectral information, resulting in clearer and more reliable detection outputs.
- Automated Feature Learning: Unlike traditional methods that require manual feature engineering, 3D CNN and autoencoders learn relevant features automatically, reducing human intervention.

- Faster Processing Speed: 3D CNN processes hyperspectral cubes efficiently by analysing spatial and spectral correlations simultaneously, leading to faster gas detection.
- Robust Performance in Complex Environments: The deep learning approach improves gas detection in challenging scenarios, such as varying atmospheric conditions and background interference.
- Generalization Capability: The trained model can be applied to different hyperspectral datasets with minimal retraining, enhancing its adaptability across various applications.
- Enhanced Visualization: The method allows for better visualization of detected gases, aiding decision-making in environmental monitoring, industrial safety, and defence applications.

4. EXPERIMENTAL ANALYSIS

Figure 1 shows a hyperspectral image taken from the AVIRIS dataset,that are representing a scene with potential gas emissions. Thesehyperspectral images serve as the input to the proposed 3D-CNN and Autoencoder-Based Gas Detection Model. The purpose of this figure is to provide a visual representation of thespectral data that the model processes to identify and classidifferent gas types.

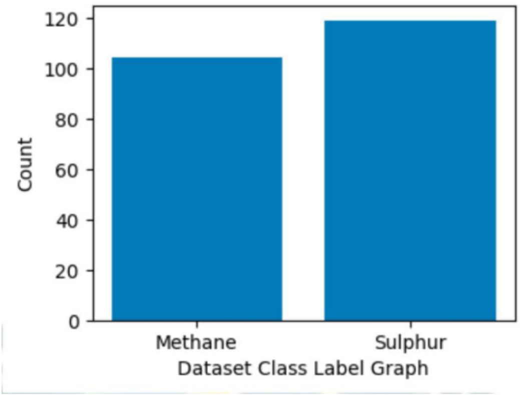
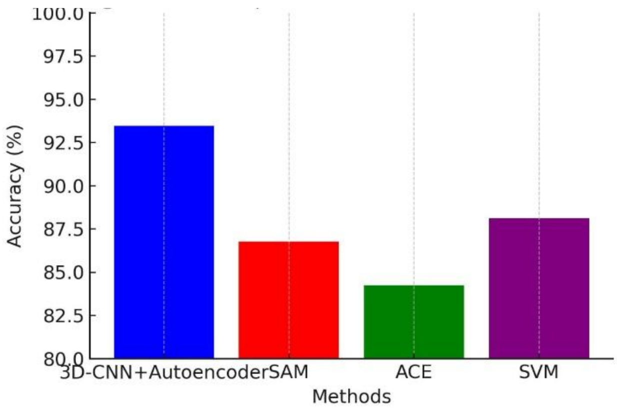
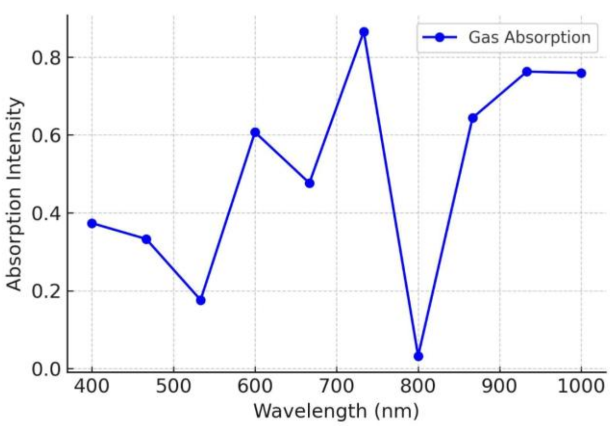


Figure: Enhanced Image





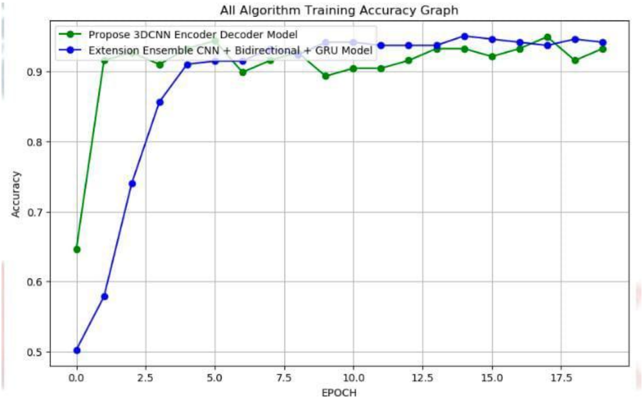


Figure: Enhanced Images

Figure 2 shows a gas emission detection heatmap generated by the proposed 3D-CNN and autoencoder-based model.Presents the gas absorption spectrum across different Wavelengths.Comparesthe accuracy of different gas detection methods, including the proposed 3D-CNN with autoencoder, Spectral Angle Mapper (SAM), Adaptive Cosine Estimator (ACE), and Support Vector Machine (SVM). The bar graph demonstrates that the proposed method achieves the highest accuracy, outperforming traditional techniques.

3D-CNN and Autoencoder Model for Gas Detection

- The proposed model integrates 3D Convolutional Neural Networks (3D-CNNs) and Autoencoders to improve gas detection accuracy in hyperspectral images.
- The 3D-CNN captures both spectral and spatial features, while the autoencoder enhances and denoises the data, improving classification performance.
- This model effectively detects and classifies gas emissions from hyperspectral images with high accuracy

5. CONCLUSION

We have proposed a deep learning-based gas detection method which combines 3D-CNN and autoencoder-based hyperspectral unmixing with neural network-based classification. The experiments reveal that a detection approach combining deep learning based unmixing with classification is better than the existing methods to handle the gas detection problem in LWIR range. An ablation study with respect to the possible different combinations for such a system, such asusing direct classification methods or using the same structure with other unmixingmethods are also performed. The proposed system combining unmixing withclassification has given better performances than direct classification withoutperforming unmixing. In addition, the 3D-CNN and autoencoder-based unmixinghas indicated better results than the conventional unmixing for the proposed gasdetection framework. The experiments have revealed that using SAM as a costfunction in the proposed method yields more successful results than the MSE metric. The performed study does not require thresholding, unlike the conventional gas detection methods. Finally, the proposed gas detection method achieves better results than state of the art gas detection methods in LWIR range due to its high learning capacity with 3-D convolutional layers. Without loss of generality, the proposed system can be adapted to different gases by integrating the target gas signature into the classification module of the proposed system in the last stage.

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