IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium | 979-8-3503-6032-5/24/$31.00 ©2024 IEEE | DOI: 10.1109/IGARSS53475.2024.10641756

A MACHINE-LEARNING APPROACH FOR GENERATING SYNTHETIC PRISMA HYPERSPECTRAL IMAGES FROM MULTISPECTRAL DATA

Manilo Monaco[1], Giorgio A. Licciardi[1], Maria L. Battagliere [1], Rocchina Guarini[1], Mario G.C.A. Cimino [2], Laura Candela[1]

[1]ASI, Italian Space Agency, Via del Politecnico SNC 00133 Roma, Italy
[2]Dept. Information Engineering, University of Pisa, L.go L. Lazzarino 1, 56122, Pisa Italy

ABSTRACT

The scarcity of a sufficiently large and representative hyperspectral image dataset is a substantial obstacle to the effective development of algorithms for remote sensing applications. Hyperspectral images can provide rich spectral information for various tasks, such as land cover classification, vegetation monitoring, and environmental assessment. However, the limited availability of diverse and well-annotated hyperspectral datasets hinders the development and optimization of these models in this domain. For this purpose, the generation of synthetic hyperspectral images has emerged as a pivotal area of research.

This paper aims to introduce a preliminary analysis of various AI-based methodologies specifically crafted to generate synthetic PRISMA hyperspectral images derived from Sentinel-2 data. By exploring innovative approaches, this study aims to develop novel techniques for creating synthetic datasets, providing valuable insights into the potential of synthetic hyperspectral imagery for algorithm training and evaluation in the absence of extensive real-world hyperspectral datasets.

Index Terms— Hyperspectral imagery, PRISMA, Artificial Intelligence, synthetic images

1. INTRODUCTION

Launched in March 2019, PRISMA (Hyperspectral PRecursor of the Application Mission) is an Earth observation satellite designed to capture high-resolution hyperspectral images of the Earth's surface, providing valuable data for various applications such as environmental monitoring, resource management, and agricultural assessment.

PRISMA's hyperspectral sensor can capture a wide range of spectral bands, from VNIR to SWIR, allowing for detailed analysis of materials and vegetation on the Earth's surface. Characterized by these features, the hyperspectral images captured by PRISMA can distinguish and analyze the Earth's surface in numerous narrow spectral bands. This capability provides valuable information about the matter composition, for tasks such as land use and land cover classification, vegetation health assessment, and identification of environmental changes over time. However, the intricate nature of hyperspectral imagery demands extensive and diverse datasets, suitable to train pattern recognition algorithms.

Various factors contribute to the challenge of the limited availability of hyperspectral training data. Primarily, obtaining hyperspectral imagery is often a complex and resource-intensive undertaking. Since PRISMA is a technology demonstrator mission, it is designed to have a revisit time of 28 days. Moreover, only under limited circumstances, it is possible to acquire off-nadir images. These limits, combined with the uncertainty of acquisition due to cloud coverage, result in a restricted pool of accessible datasets, causing limitations on applications that require frequent and timely monitoring of dynamic and rapidly changing phenomena on the Earth's surface.

Thus, the above limits on hyperspectral images constrain several advanced applications based on hyperspectral remote sensing.

To mitigate this problem, the Italian Space Agency, through the IRIDE program intends to launch in the next years a constellation of hyperspectral satellites that will considerably improve the revisit time. However, having a good revisit time may not be sufficient because of the cloud coverage.

A valuable solution in scenarios where actual hyperspectral imagery may be limited or unavailable is the generation of synthetic hyperspectral images, i.e., the creation of artificial datasets with spectral characteristics like those found in real-world hyperspectral imagery. This approach allows training machine learning models, algorithm development, and testing without expensive ground truth hyperspectral datasets.

However, to ensure the suitability for specific applications, it's crucial to validate the accuracy and reliability of the synthetic hyperspectral images against real-world hyperspectral data. For these reasons, it is essential to generate synthetic data with a physical interpretation for target applications. This requirement suggests that the synthetic images should derive from other Earth Observation data with higher revisit times, such as Sentinel-2 or Landsat 8/9 multispectral images.

Several methodologies exist for generating synthetic hyperspectral images from multispectral data, often relying on machine learning and image processing approaches:

i. *Spatial-Spectral Modeling*. Techniques that combine spatial and spectral information, often called spatial-spectral modeling, can be employed. These models consider the spatial relationships between pixels and the spectral characteristics to simulate additional spectral bands [1-3].
ii. *Deep Learning and Neural Networks.* Advanced techniques, such as deep learning and neural networks, can be trained on existing hyperspectral datasets to learn complex relationships between multispectral bands and corresponding hyperspectral bands. Once trained, these models can generate synthetic hyperspectral images from new multispectral inputs. Among the Deep Learning approaches, it is worth mentioning Generative Adversarial Networks (GANs). GANs, a type of generative model, can be utilized for generating synthetic hyperspectral images. GANs consist of a generator that creates synthetic data and a discriminator that distinguishes between real-world and synthetic data. Through an adversarial training process, the generator improves its ability to produce realistic hyperspectral images [4-5]..
iii. *Band Interpolation*. Simple interpolation methods can be employed to estimate values for spectral bands not captured by multispectral data. These methods use existing bands as references to infer values for intermediate bands, effectively creating a denser spectral dataset [6].

This study aims to analyze the effectiveness of different AI-based approaches to generate PRISMA-like hyperspectral images from multispectral images.

2. MATERIALS AND METHODS

Synthetic hyperspectral image generation methods have been significantly transformed by the rise of machine learning. Indeed, machine learning is particularly suitable for unraveling and capturing the complexities inherent in spectral patterns and intricate relationships between hyperspectral and multispectral data.

In the realm of hyperspectral imaging, achieving various spectral bands is crucial for a comprehensive analysis, and the limits of real-world datasets have spurred the exploration of novel methodologies. Neural Networks, especially Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), have demonstrated exceptional capabilities in reproducing the spectral characteristics of hyperspectral datasets and in generating additional synthetic bands. These capabilities enable the creation of rich hyperspectral imagery, fostering a more comprehensive understanding of the Earth's surface complexities.

This study compares different types of deep-learning approaches, namely GANs, CNNs, and deep feed-forward neural networks (FFNNs).

2.1. Generative Adversarial Networks

Generative Adversarial Networks have emerged as a powerful and innovative approach for generating hyperspectral images, providing a means to provide realistic and high-dimensional spectral data. A GAN consists of two neural networks – a generator and a discriminator – engaged in an adversarial training process.

The task of the generator network is to produce synthetic hyperspectral images from multispectral data. Trained on provided Landsat or Sentinel-2 datasets, the generator learns to capture the complex relationships between different spectral bands and generate synthetic bands that resemble those available in real-world hyperspectral imagery.

The discriminator network, in contrast, is designed to differentiate between real-world hyperspectral images and synthetic ones created by the generator. This adversarial setup provides a feedback loop where the generator strives to produce synthetic images that are increasingly indistinguishable from real-world hyperspectral scenes.

2.2. Convolutional Neural Networks

Applying Convolutional Neural Networks to the generation of synthetic hyperspectral images from multispectral data requires a sophisticated and effective approach within the domain of remote sensing and Earth observation [7].

CNNs, known for their capability in extracting hierarchical features from image data, are leveraged to create synthetic datasets that emulate the spectral richness of authentic hyperspectral scenes derived from multispectral observations.

The reference architecture is composed of two fundamental parts: a recurrent neural network, which provides an internal sequential representation of the multispectral signal, and a decoder (or generative network) that converts the internal representation into the hyperspectral signal.

The recurrent neural network can preserve the ordering of the original signal along the spectral dimension and is responsible for transforming the signal into a representation more suitable for processing by the decoder.

The decoder, composed of mono-dimensional transposed convolutional layers, upsamples the signal and models the correlations between the narrower bands of the hyperspectral signal.

2.3. Feed-Forward Neural Networks

The simplest approach to generate synthetic hyperspectral images using multispectral data is based on deep feed-forward neural networks. This type of neural network, also known as a multi-layer perceptron (MLP), is designed to learn complex mappings between multispectral input data and the corresponding hyperspectral output.

The deep feed-forward neural network consists of multiple layers, including an input layer, several hidden layers, and an output layer. The availability of multiple hidden layers enables the network to capture intricate patterns and relationships within the input multispectral data.

3. EXPERIMENTAL STUDIES

Synthetic PRISMA hyperspectral images have been derived using the CNN, GAN, and FFNN approaches, respectively. Both Sentinel-2 and Landsat-8 images have been used as input for the abovementioned techniques.

A first qualitative analysis has been carried out on a synthetic PRISMA image obtained from a Sentinel-2 image. Fig. 1 and Fig.2 show the RGB image obtained from the original and the synthetic PRISMA data, respectively.

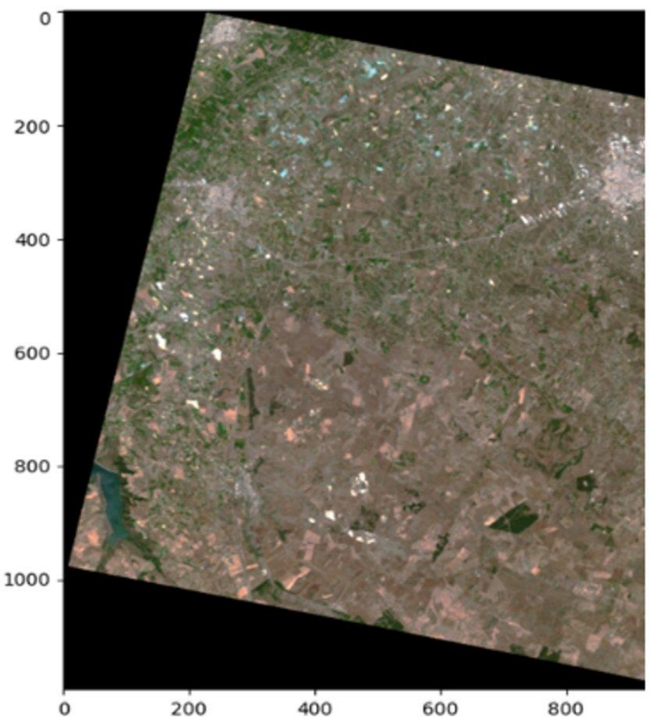

Figure 1: RGB images generated from the original PRISMA data

A further analysis has been carried out by comparing the average spectral signatures of the two images, as depicted in Fig. 3.

In order to quantitatively assess the similarity between the original hyperspectral image and the one generated with the reference neural architecture, two metrics have been considered, namely ERGAS and SAM, capable of measuring spatial and spectral distortions. The *Table 1* shows the values measured on a sample image. The original image has been acquired by PRISMA satellite on 20/06/2022, whereas the multispectral image, used to generate the synthetic hyperspectral image, has been acquired by Sentinel 2 satellite on 21/06/2022.

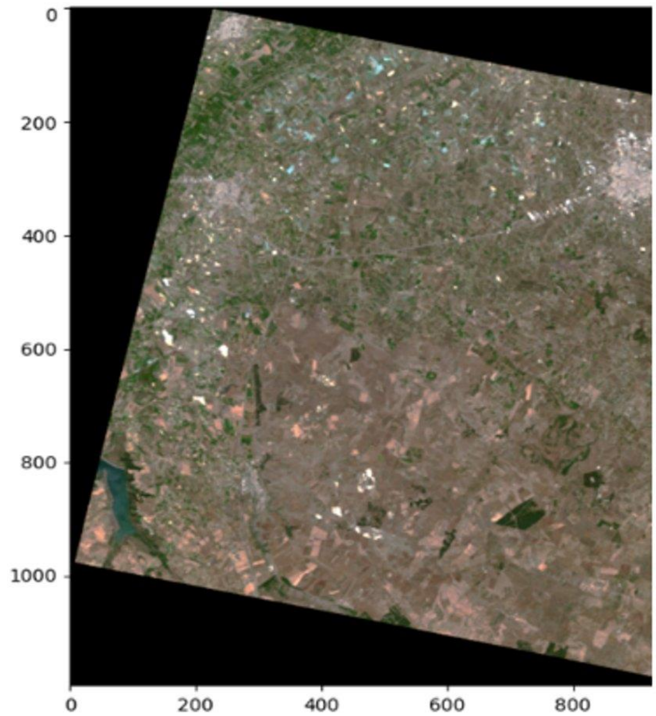

Figure 2: RGB images generated from the synthetic PRISMA data

The purpose of this paper is to introduce a novel perspective in the field of PRISMA synthetic hyperspectral images based on machine learning. A small case study has been briefly discussed to show the potential of the approach. Further research is necessary to achieve significant results. To this aim, future work will focus on further experimentation and investigation, as well as on further integration with other methods. Moreover, quantitative performance indicators could be developed, based on other similarity metrics.

Table 1 - Similarity scores between original and synthetic hyperspectral images

Metric	Similarity score
ERGAS	8.6412
SAM	0.2641

4. CONCLUSIONS

In this paper, three machine learning architectures have been considered for the synthetic generation of hyperspectral data from multispectral data, having as a reference PRISMA data: GANs, CNNs, and deep feed-forward neural networks (FFNNs). The effectiveness of these advanced techniques lies in their ability to discern and learn complex patterns inherent

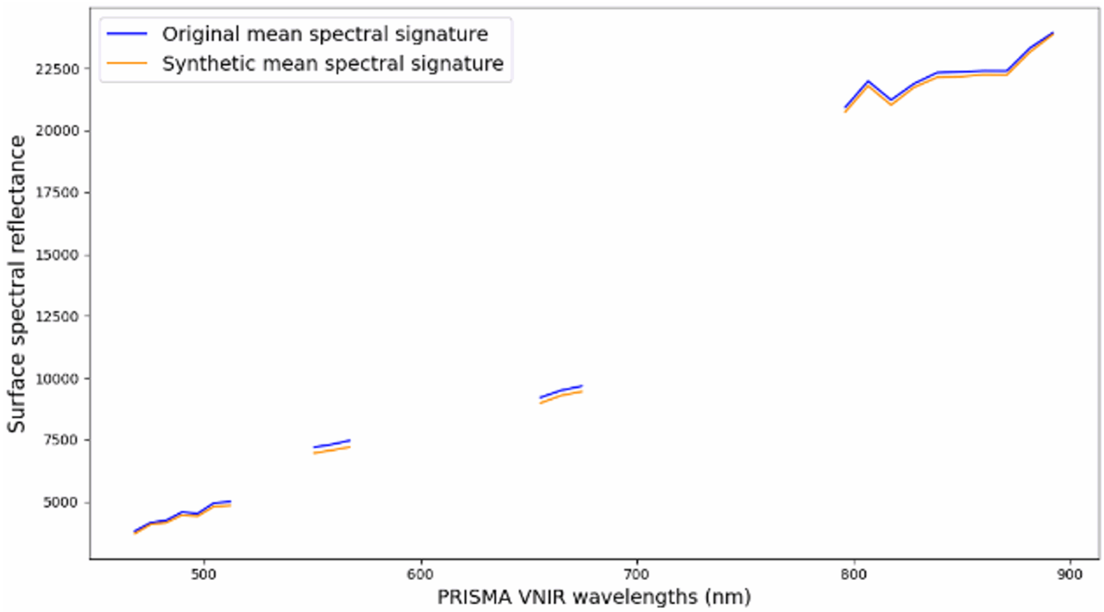

Figure 3: Average spectral signatures of an urban area, obtained from the original and the synthetic PRISMA images, respectively

in hyperspectral data, leading to the generation of synthetic images that closely emulate the characteristics of real-world hyperspectral scenes. This artificial augmentation of spectral information has proven invaluable in scenarios where authentic hyperspectral datasets are limited, offering researchers and practitioners a diverse and extensive dataset for training, testing, and refining algorithms tailored for hyperspectral image analysis.

Although a more in-depth exploration of the approaches, and an enrichment of the benchmark are needed, the early experimental studies are promising. An extensive study in this direction can be a future work to bring a contribution to the field.

ACKNOWLEDGEMENTS

Work supported by the Italian Ministry of Education and Research (MIUR) in the framework of the Project “TEBAKA – TErritory Basic Knowledge Acquisition” - PON “Research and Innovation” 2014-2020. Project carried out using ORIGINAL PRISMA Products - © Italian Space Agency (ASI); the Products have been delivered under an ASI License to Use. Work partially supported by: (i) the University of Pisa, in the framework of the PRA 2022 101 project “Decision Support Systems for territorial networks for managing ecosystem services”; (ii) the European Commission under the NextGenerationEU program, Partenariato Esteso PNRR PE1 - "FAIR - Future Artificial Intelligence Research" - Spoke 1 "Human-centered AI"; (iii) the Italian Ministry of Education and Research (MIUR) in the framework of the FoReLab project (Departments of Excellence).

REFERENCES

[1] G. Licciardi, M. A. Veganzones, M. Simões, J. Bioucas and J. Chanussot, "Super-resolution of hyperspectral images using local spectral unmixing," 2014 6th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS), Lausanne, Switzerland, 2014, pp. 1-4

[2] Schott, J.R., Brown, S.D., Raqueño, R.V., Gross, H.N., & Robinson, G. 1999. An advanced synthetic image generation model and its application to multi/hyperspectral algorithm development, Canadian Journal of Remote Sensing, Vol. 25, No.2, pp. 99-111, June 1999.

[3] Guanter, L., Segl, K., & Kaufmann, H. (2009). Simulation of optical remote-sensing scenes with application to the EnMAP hyperspectral mission. IEEE Transactions on Geoscience and Remote Sensing, 47(7), 2340-2351.

[4] Liu, W.; You, J.; Lee, J. HSIGAN: A Conditional Hyperspectral Image Synthesis Method with Auxiliary Classifier. IEEE J. 1-2]. Top. Appl. Earth Obs. Remote Sens. 2021, 14, 3330–3344.

[5] Goodfellow, I.J.; Pouget-Abadie, J.; Mirza, M.; Xu, B.; Warde-Farley, D.; Ozair, S.; Courville, A.; Bengio, Y. Generative Adversarial Nets. In Proceedings of the 27th International Conference on Neural Information Processing Systems, Cambridge, MA, USA, 8–13 December 2014; Volume 2, pp. 2672–2680

[6] Hoang, Nguyen & Koike, Katsuaki. (2017). Transformation of Landsat imagery into pseudo-hyperspectral imagery by a multiple regression-based model with application to metal deposit-related minerals mapping. ISPRS Journal of Photogrammetry and Remote Sensing. 133. 157-173. 10.1016/j.isprsjprs.2017.09.016.

[7] Paul, S., & Kumar, D. N. (2020). Transformation of multispectral data to quasi-hyperspectral data using convolutional neural network regression. IEEE Transactions on Geoscience and Remote Sensing, 59(4), 3352-3368.