Defense Systems
Information Analysis Center

DSIAC TECHNICAL INQUIRY (TI) RESPONSE REPORT

Infrared (IR) Hyperspectral Imagery From IR Multispectral Sensors

Report Number:

DSIAC-BCO-2025-680

Completed April 2025

DSIAC is a U.S. Department of Defense Information Analysis Center

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*
30-04-2025

2. REPORT TYPE
Technical Research Report

3. DATES COVERED *(From – To)*

4. TITLE AND SUBTITLE

Infrared (IR) Hyperspectral Imagery From IR Multispectral Sensors

5a. CONTRACT NUMBER
FA8075-21-D-0001

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

6. AUTHOR(S)

Amit Banerjee

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

Defense Systems Information Analysis Center (DSIAC)
SURVICE Engineering Company
4695 Millennium Drive
Belcamp, MD 21017-1505

8. PERFORMING ORGANIZATION REPORT NUMBER

DSIAC-BCO-2025-680

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

Defense Technical Information Center (DTIC)
8725 John J. Kingman Road
Fort Belvoir, VA 22060-6218

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT

Distribution Statement A. Approved for public release: distribution is unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

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This report provides a review of ML algorithms that leverage color (red, green, blue) data to reconstruct hyperspectral imagery. There are two classes of algorithms that are reviewed here. The first is the classical, prior-information-based methods that utilize dictionary and manifold-learning techniques to reconstruct hyperspectral signatures from three-channel color data. The second relies on deep-learning methods that use neural networks to learn the mapping from color to hyperspectral using training data and supervised learning. These approaches are summarized, and their relative advantages and disadvantages are discussed. Finally, a plan is outlined to extend current work from visible and near-infrared (IR) data to IR imagery.

15. SUBJECT TERMS
hyperspectral imaging, machine learning, deep learning, hyperspectral image reconstruction

16. SECURITY CLASSIFICATION OF: U

a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
U	U	U	UU	19	Ted Welsh, DSIAC Director

19b. TELEPHONE NUMBER *(include area code)*
443-360-4600

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39.18

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TI Research

A chief service of the DoDIAC is free technical inquiry (TI) research limited to four research hours per inquiry. This TI response report summarizes the research findings of one such inquiry. Given the limited duration of the research effort, this report is not intended to be a deep, comprehensive analysis but rather a curated compilation of relevant information to give the reader/inquirer a "head start" or direction for continued research.

Defense Systems Information Analysis Center

Abstract

Hyperspectral imaging systems are able to address critical challenges, ranging from detecting chemical, biological, radiological, nuclear, and explosives materials to identifying targets from remote distances. However, due to their complexity, these sensors are expensive to build, maintain, and operate. A promising solution that has been recently explored is to leverage the abundance of inexpensive and mature multispectral cameras to reconstruct hyperspectral images via machine-learning (ML) software.

This report provides a review of ML algorithms that leverage color (red, green, blue) data to reconstruct hyperspectral imagery. There are two classes of algorithms that are reviewed here. The first is the classical, prior-information-based methods that utilize dictionary and manifold-learning techniques to reconstruct hyperspectral signatures from three-channel color data. The second relies on deep-learning methods that use neural networks to learn the mapping from color to hyperspectral using training data and supervised learning. These approaches are summarized, and their relative advantages and disadvantages are discussed. Finally, a plan is outlined to extend current work from visible and near-infrared (IR) data to IR imagery.

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1.0 TI Request

1.1 Inquiry

Can infrared (IR) hyperspectral imagery be acquired from IR multispectral sensors?

1.2 Description

The Defense Systems Information Analysis Center was asked to explore the use of computational imaging for IR hyperspectral sensors. The U.S. Department of Defense and intelligence community exploit hyperspectral imaging for challenges ranging from detecting chemical, biological, radiological, nuclear, and explosives (CBRNE) materials to identifying targets from remote distances. However, hyperspectral sensors are often optically and mechanically complex systems, making them expensive to build and operate. An intriguing solution to this challenge is to reconstruct hyperspectral data from simpler multispectral cameras that are based on mature technology and easier to operate.

2.0 TI Response

2.1 What Is Hyperspectral Imaging?

Hyperspectral remote sensing (Figure 1), also known as imaging spectroscopy, is typically used to identify terrestrial vegetation, minerals, and land-use/land-cover mapping. It is based on the examination of many narrow-bandwidth spectral channels to identify unique spectral features across the electromagnetic spectrum. A typical hyperspectral scanner records over hundreds of narrow-bandwidth channels, which enables the construction of a continuous reflectance spectrum for each pixel. Common applications of hyperspectral remote sensing include:

- Target Detection: Given the spectral signature of a target or material, use spectral matching algorithms to detect it in a hyperspectral image (HSI) [1–2].
- CBRNE Applications: Use spectral-matching algorithms to detect and identify chemical plumes and illicit materials and other signatures for CBRNE threats.
- Medical Imaging: Use spectral features to detect diseased tissue and biomarkers for disease and to monitor blood flow in human and animal tissue [3–4].
- Environmental Monitoring: Observe atmospheric parameters such as water vapor; cloud properties; aerosols; and littoral parameters like estimating chlorophyll, phytoplankton, dissolved organic materials, or suspended sediments.

2.2 What Is Computational Hyperspectral Imaging?

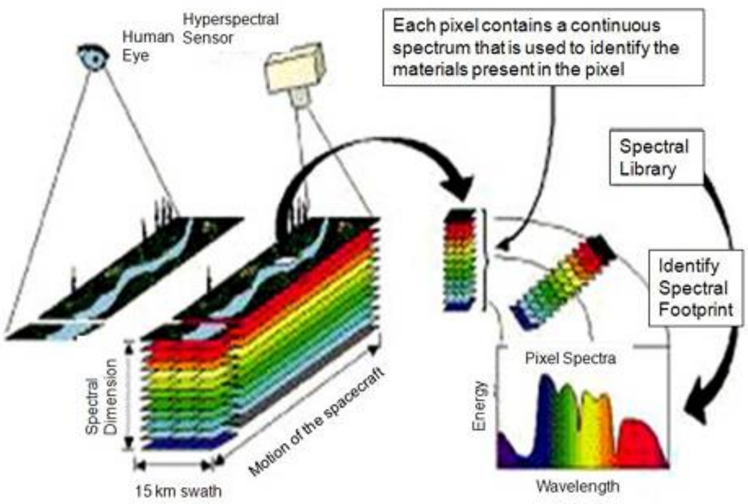

Figure 1. Illustration of Hyperspectral Remote Sensing [5].

As mentioned previously, hyperspectral sensors are often optically and mechanically complex systems, making them expensive to build and operate. An intriguing solution to this challenge is to reconstruct hyperspectral data from simpler red, green, blue (RGB) cameras that are based on mature technology and easier to operate. Recent work [6–9] has shown that machine-learning (ML) algorithms can be used to learn the mapping from color (RGB) data to hyperspectral measurements. The earlier work [10, 11] is based on dictionary- and manifold-learning techniques to reconstruct hyperspectral signatures from three-channel color data**Error! Reference source not found.**. The state of the art [12–14] relies on deep learning (DL) neural networks that learn the mapping from color to hyperspectral using training data and supervised learning. Figure 2 provides an illustration of the process of converting HSIs to color and reconstructing hyperspectral data from color images. These reconstruction methods obviate the need for expensive and specialized hardware, while providing high spectral resolution imagery [15].

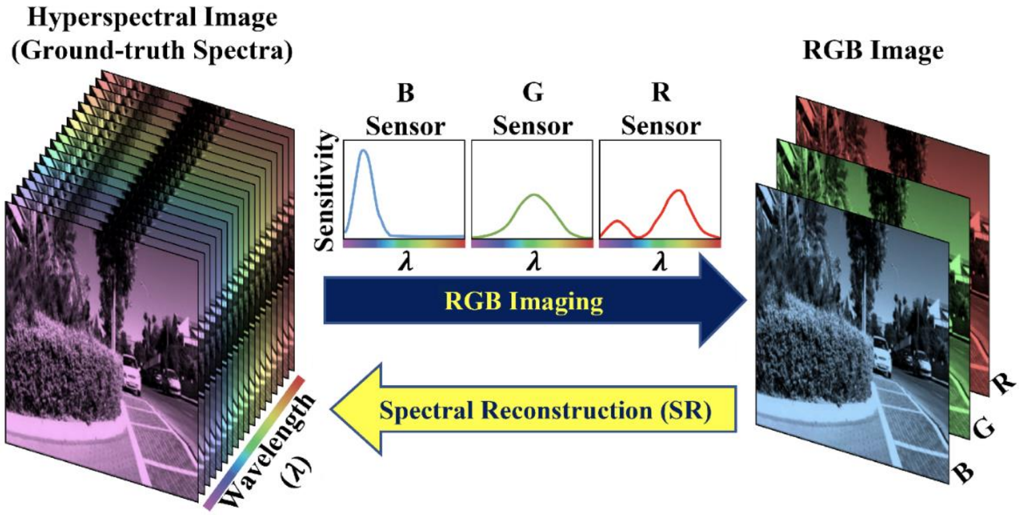

Figure 2. Illustration of the Process of Converting HSIs to Color and Reconstructing Hyperspectral Data From Color Images [16].

2.3 Survey of Computational Hyperspectral Imaging Methods

Algorithms for constructing hyperspectral data from multispectral imagery can be classified into two categories: (1) prior-based and (2) data-driven methods. The first class of methods exploits statistical information in the data to represent and reconstruct the inherent spectral attributes of the image. The data-driven algorithms use training data to learn the mapping between color and hyperspectral imagery.

2.3.1 Prior-Based Methods

These methods use linear algebra and optimization theory to estimate high-resolution spectra of an image from its color image. The color and high-resolution spectra are each represented by two-dimensional matrices, and the transformation between the two is learned by exploiting prior knowledge about the scene.

There are two classes of such algorithms: (1) dictionary learning and (2) manifold learning. Dictionary learning exploits the spectral and spatial sparsity of hyperspectral data to efficiently represent the spectra as a linear combination of basis spectra. An overcomplete set of basis spectra are found by combining prior knowledge of the scene and through dictionary learning [17]. Using an overcomplete set ensures that a sparse representation exists, which allows for a unique solution to be found via minimization of the L_1 loss function.

Manifold learning also exploits the sparse nature of spectral data. The sparsity implies that the high-dimensional spectral data lie in a lower-dimensional manifold. The lower-dimensional manifold is easier to interpret and analyze. As an example, for spectral reconstruction [18], a manifold-learning method [19] has been used "to simplify the three-to-many mapping problem into a three-to-three problem" [15] via an isometric mapping.

The performance of prior-based methods suffers from two key problems. The first is that they require prior knowledge about the scene, which limits their use and requires domain expertise. The second is that these methods only consider information in the spectral domain and ignore the spatial information that is critical and abundant in imagery [15]. As a result, the reconstructed spectra often miss key features and the spatial correlations are not maintained.

2.3.2 Data-Driven Methods

Prior-based methods rely on simplifying assumptions and prior knowledge that limit their effectiveness. To address these issues, researchers have developed DL methods that leverage large amounts of training data and the state of the art in ML to learn the mapping from color or multispectral images to hyperspectral data. These DL methods can be grouped according to the type of networks used to learn the mapping.

2.3.2.1 Linear Convolutional Neural Network (CNN). Linear CNN are standard CNN architectures that learn the mapping between the input RGB data and the output hyperspectral data [15]. More information on linear CNNs can be found in the literature [12, 20–23].

2.3.2.2 U-Net. U-Net models are based on an encoder/decoder structure. RGB images are input to the encoder to a lower-dimensional latent space. The decoder then maps the latent features to high-dimensional spectral images. Unfortunately, U-Nets typically emphasize "the spatial information and the spectral features are usually ignored or treated as another spatial dimension," thereby lowering the quality of the spectral reconstruction [15].

2.3.2.3 The Generative Adversarial Network (GAN). The GAN is one of the first generative AI models for imagery. It uses game theory to teach a generator (to generate hyperspectral images) via a discriminator that is trained to learn the differences between real and reconstructed hyperspectral data. This work was the precursor to attention networks, which are the latest generative models used to reconstruct spectral imagery. More information can be found in the literature [24–29].

2.3.2.4 Residual and Dense Networks. These networks utilize deep and densely connected layers with skip connections to learn a richer feature representation and mapping between the color and hyperspectral imagery [15]. They also have the advantage of increased training stability by alleviating the vanishing-gradient problem [30, 31].

2.3.3 Comparison and Analysis

A summary comparing the pros and cons of prior-based and data-driven methods for spectral reconstruction is provided in Table 1.

Table 1. Comparing Prior-Based and Data-Driven Methods for Spectral Reconstruction

Class of Algorithms	Advantages	Disadvantages
Prior Based	• Directly exploits prior knowledge to reconstruct hyperspectral data • Can incorporate domain expertise into spectral reconstruction	• Ignores spatial texture and information, leading to loss of high-frequency features • Relies on hand-crafted priors, leading to poor generalization across sensors and image backgrounds
Data Driven	• Can exploit spectral and spatial features for hyperspectral reconstruction • Can learn more accurate and complex mappings between RGB and hyperspectral data by using DL • By training a single model across multiple sensors and datasets, can achieve greater generalization	• Requires large amounts of training data, which are often unavailable

2.4 Future Research Considerations

This section discusses network architecture, loss function, resolving dataset issues, and learning strategies that may be considered for future research.

2.4.1 Network Architecture

A robust model for mapping RGB imagery to hyperspectral data should exploit spatial and spectral features, as well as local and global spatial context at various resolutions. These factors go into the design of the network, which is an outstanding research challenge. For example, "combining attention mechanisms of key features can enhance the production of interested details [and] the combination of hierarchical structure and attention mechanism can make the network more enhanced with feature representation ability" [15].

2.4.2 Loss Function

DL methods are trained to optimize different loss functions, depending upon the problem they are trying to solve. For image reconstruction, most models use the L_1 or L_2 loss function to minimize the pixel differences between the ground-truth and reconstructed images. However, these models do not consider the spatial context and optimize for each pixel independently. This problem is exacerbated when considering the spectral features that need to be accurately represented.

The problem of deriving a cost function that jointly optimizes for the pixel-level, spatial, and spectral properties when reconstructing the hyperspectral image has not been sufficiently addressed. This is perhaps the primary outstanding challenge that needs to be resolved for accurate spectral estimation.

2.4.3 Resolving Dataset Issues

DL models require large amounts of hyperspectral data. Such datasets are often not available, particularly labeled data with associated color or multispectral imagery. The performance of DL models is known to be brittle and unreliable when trained on limited data.

To alleviate this problem, two types of data augmentation can be exploited. The first approach leverages spatial information by cropping, flipping, and rotating images that are used to augment the training data. Similar augmentation methods need to be found for the spectral domain. The second strategy is to use simulated hyperspectral data. By adding synthetic data to real data, the amount of training data can easily be increased to help generalize the performance of the model. To minimize the risk of combining synthetic and real data, ML models that map synthetic data to real imagery can be utilized, thereby reducing the domain shift between the data and helping speed up the convergence of the model during training.

2.4.4 Learning Strategies

Supervised learning is the most commonly used approach to train DL methods for hyperspectral image reconstruction. However, they require fully labeled datasets, which is not often possible due to the cost of collecting and curating the data. Unsupervised, semi-supervised, and self-supervised learning are well-known approaches to address these challenges. They can help improve the performance of spectral reconstruction algorithms, even with limited fully labeled training data.

2.5 Extending to IR Hyperspectral Imaging

The latest advances in computational hyperspectral imaging are promising and suggest new lines of future work. For example, the lessons learned for developing these techniques in the visible and near-infrared (VNIR) wavelengths can be extended to the short-wave infrared (SWIR) and long-wave infrared (LWIR) regimes.

The network architecture and approaches for training these models should translate well from the VNIR to the SWIR. This is because physics is similar (reflectance spectroscopy). There could be additional considerations when translating to LWIR, since physics is different (reflectance vs. emissive).

The biggest challenge is generating training data. The availability of SWIR and LWIR sensors is clearly more limited when compared to VNIR cameras. Government organizations will need to partner with industry to identify the sensors (both multi- and hyperspectral) that will be necessary to concurrently collect enough imagery to train the DL models. Furthermore, the teams will need to investigate the use of synthetic data, as there are well-known image-rendering tools that can generate multi- and hyperspectral scenes. The goal is to use these images to augment the training data's sets. Another key challenge is to overcome the gap between synthetic and real spectral imagery. Already, there are artificial intelligence tools, such as GANs and variational autoencoders that can minimize the distribution shifts between real and synthetic data. These can help improve the quality and quantity of the training data, which is critical for the success of these models to reconstruct hyperspectral imagery from multispectral imagery.

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Biography

Amit Banerjee is the chief hyperspectral architect for QinetiQ, USA. He is a senior scientist and engineer with extensive experience in remote sensing, computer vision, and machine learning. At QinetiQ, he leads and coordinates the research team in developing artificial-intelligence for hyperspectral image exploitation. After receiving his Ph.D. in electrical engineering from the University of Maryland in 2000, he joined The Johns Hopkins University Applied Physics Laboratory. He developed novel solutions for hyperspectral remote sensing and explored the use of spectral measurements for video surveillance. He served as the principal investigator on multiple programs for the National Geospatial-Intelligence Agency, the Defense Advanced Research Projects Agency, and the U.S. Air Force. He has also contributed to deployed systems for the U.S. Navy and U.S. Special Operations Command. Dr. Banerjee also teaches in the graduate-level electrical-engineering program at The Johns Hopkins University and is a senior member of the Institute of Electrical and Electronics Engineers.

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