Statistical Learning for Satellite Hyperspectral Images

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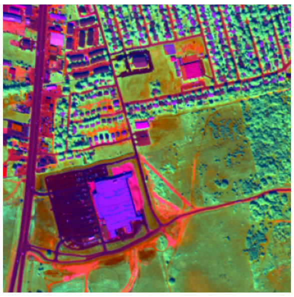
21/09/2025

Keywords: hyperspectral imaging, statistical learning, spectral unmixing, high-dimensional statistics, segmentation

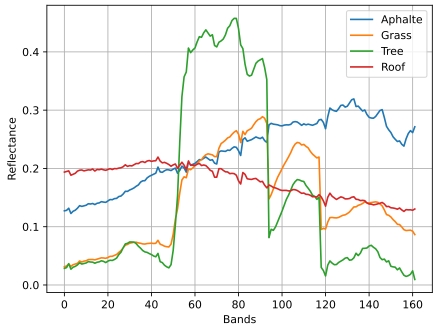
1 Context

Hyperspectral imaging records several hundred narrow, contiguous bands across the visible and infrared spectrum. This results in high-dimensional data that carry rich spectral information. However, the relatively low spatial resolution means that several distinct materials may coexist within a single pixel. These elementary materials are referred to as *endmembers*.

A fundamental problem is therefore *spectral unmixing*, which aims to recover both the spectral signatures of the endmembers and their relative proportions in each pixel. Several methods have been developed, relying on geometry [11, 12], optimization [14, 13], or machine learning [15, 16]. However, only a few studies, such as [17, 3], have been devoted to designing a consistent statistical framework that provides physically meaningful results while also quantifying the uncertainty of the solution. Some fully Bayesian methods have been proposed [10], but they often suffer from high computational cost, strong noise assumptions, reliance on dimensionality reduction, and potential identifiability issues. To overcome these limitations, we propose to leverage recent advances in random matrix theory and high-dimensional statistics [5, 1, 7, 8] to design a statistical method adapted to the high-dimensional nature of hyperspectral data. This approach exploits the covariance structure between neighboring pixels.



(a) Urban hyperspectral scene.



(b) Example of extracted endmembers.

Figure 1: Illustration of a hyperspectral image and its endmembers.

2 Previous Work and Objectives

The project aims to advance statistical learning for hyperspectral satellite images through the following objectives:

- **Estimation of the number of endmembers:** In an initial study [9], we proposed a consistent statistical method to estimate the number of endmembers in each pixel. While several approaches have been introduced in the literature [2, 3, 4], they often rely on inconsistent covariance estimators in the high-dimensional regime. Our method explicitly accounts for both the high dimensionality of hyperspectral data and the correlations between adjacent spectral bands.

- **Hyperspectral unmixing:** Building on the first objective, we aim to develop a comprehensive methodology for spectral unmixing that accounts for the high-dimensional nature of the data. The approach will rely on parametric models for the endmember spectra that satisfy regularity conditions, ensuring physical interpretability. This line of work will be developed in connection with [8].

- **Machine learning for hyperspectral data:** Finally, we seek to design machine learning algorithms specifically adapted to hyperspectral data. These algorithms will take into account high dimensionality, low-rank structures, and correlated noise to enable efficient segmentation and classification. A preliminary step in this direction has been presented in [6].

3 Information and Contact

This Ph.D. project takes place at the Laboratoire de l'Intégration du Matériau au Système (IMS), Bordeaux University, with the following team:

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