Deep learning based approaches for hyperspectral imaging: application to non-destructive control

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1 Context

Hyperspectral imaging is traditionally associated with remote sensing applications. This modality of imaging is however increasingly used in novel applications including surface characterization, defects detection or non destructive control. The optical interactions leading to the hyperspectral observations in these new applications of hyperspectral imaging are very different to the ones classically occuring in remote sensing, which foster the development of dedicated data processing methods to process them. A hyperspectral sensor collects information in the form of a set of spatial images where each image corresponds to a narrow band of wavelengths of the electromagnetic spectrum. Its spatial resolution is a key characteristic of the sensor: when pixels are too large, the measured spectra is usually a combination of multiple elementary materials present in the observation scene. In this situation, sophisticated post-processing methods have to be applied to identify these materials. The development of these methods has led to the emergence of an active field of research referred to as hyperspectral unmixing (HU). HU algorithms aim at identifying the *spectral signatures* or *endmembers* of the elementary materials and at quantifying their relative contributions or *abundances* to the hypersensor measurements.

A classical approach in HU is to assume that the measured spectra are linear combinations of the endmembers present in the observed surface weighted by their respective abundances. The linear mixing model has a straightforward physical interpretation: it corresponds to situations where each incoming light ray only interacts with a single endmember before reaching the sensor. A large corpus of methods based upon geometrical or statistical approaches have been considered to solve the problem of linear unmixing, which is now relatively well understood [3]. Still, a number of problems remain open:

- *Endmembers variability.* The spectral signatures of the elementary materials often exhibit intrinsic variability within the observations. The issue of endmembers variability is still an active ongoing research topic in HU.

- *Highly mixed observations.* When the mixing is linear, the hyperspectral observations are embedded in a low-dimensional simplex. Geometrical methods try to identify this simplex by assuming the presence of observations either at the vertices or at the boundary of the simplex. These assumptions are however not satisfied when the observations are highly mixed.

- *Nonlinear mixing models.* In situations where the incoming electromagnetic wave interacts with more than one material present at the scene, the mixing model is usually nonlinear.

These issues are particularly present in non-destructive control applications, due to the intrinsic variability of industrial conditions and to the non-linearity of the optical model leading to the hyperspectral observations.

2 Objective of the PhD

The development of algorithms accounting for the aforementioned issues is an essential prerequisite for a wider use of hyperspectral imaging in industrial applications. Recently, deep learning architectures have been increasingly used to process hyperspectral observations. The ambition of this PhD proposal is to develop a unified mathematical framework for HU accounting for the non-linearity of the mixing model, the variability of the endmembers and the potentially high level of mixing within the observations. We will consider in particular the use of variational autoencoder (VAE) architectures [4], which has not been explored in depth so far in the context of hyperspectral unmixing. We plan to validate the methodology on classical datasets of hyperspectral observations, usually related to the linear mixing model but for which endmember variability is often present within the observations [3], as well as on industrial data.

3 Required skills

The preferred candidate should have a solid understanding of mathematics and familiarity with programming languages, as well as experience using deep learning tools like Tensorflow or PyTorch. Additionally, they should demonstrate a keen interest in conducting research within the realms of mathematics and image processing.

4 Contact and supervision

The Center for Mathematical Morphology (CMM) is part of Mines Paris, PSL University, and is located in Fontainebleau, France (40 minutes from Paris by train), near the castle and the forest. Flexibilityin the workplace is also possible. Please send your application (CV and short motivation letter) to Bruno Figliuzzi (bruno.figliuzzi-at-minesparis.psl.eu).

References

[1] Tarek Zenati, Bruno Figliuzzi, and Shu Hui Ham. Characterization of surface oxides from hyperspectral measurements. In *2022 12th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS)*. IEEE, 2022.

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[3] José M Bioucas-Dias, Antonio Plaza, Nicolas Dobigeon, Mario Parente, Qian Du, Paul Gader, and Jocelyn Chanussot. Hyperspectral unmixing overview: Geometrical, statistical, and sparse regression-based approaches. *IEEE journal of selected topics in applied earth observations and remote sensing*, 5(2):354–379, 2012.

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