Hybrid computational methods for hyperspectral image analysis

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Outline

1. Introduction
2. Dimensionality reduction
3. Spectral unmixing

Motivation

- Provide a brief review of recent advances in computational methods for hyperspectral image analysis with emphasis in hybrid approaches.
- Hyperspectral imagery acquisition and analysis are growing fields.
- The analysis of hyperspectral images will have an increasing impact in several application areas, i.e., Earth observation, planetology, food industry, quality processes, medicine, etc.
- Hyperspectral image analysis is itself a hybrid process that chains different computational techniques.
- We focus on dimensionality reduction and spectral unmixing which are fundamental parts of hyperspectral image analysis.

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Hyperspectral imaging

- Spectral imaging refers to the collection of **optical images taken in multiple wavelength bands** that are aligned such that at each pixel there is a vector representing the response to the same spatial location for all wavelengths.

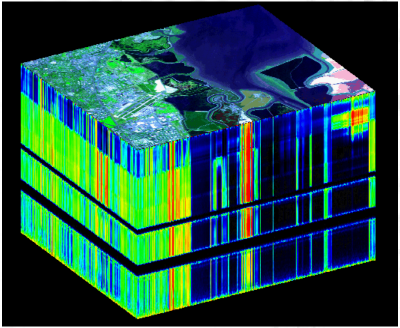
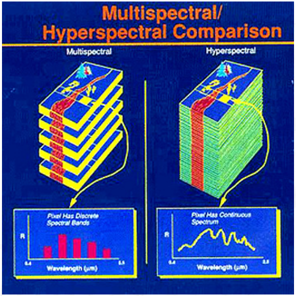


Figure: AVIRIS airborne sensor hyperspectral cube

Hyperspectral Vs. Multispectral

- Hyperspectral imaging systems (HSI) differ from color and multispectral imaging systems (MSI) in:
  - Number of bands: 3-10 (MSI) / 100+ (HSI).
  - Spectral resolution: order of 10 (MSI) / order of 100 (HSI).
  - Contiguity: widely and irregularly spaced bands (MSI) / contiguous and regularly spaced bands.



* Image by Wikipedia

Hyperspectral analysis

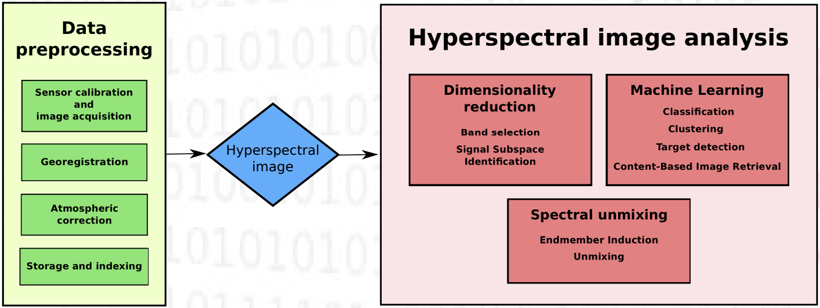


Figure: Diagram of an hyperspectral image analysis process.

Dimensionality reduction

- Dimensionality reduction (DR) is often the first step in the hyperspectral analysis given the high spectral dimensionality of hyperspectral data.
- In DR we try to find a low-dimensional optimal representation of the hyperspectral data that could be easily analyzed.
- Two ways:
  - Subspace identification
  - Band selection

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- Two ways:
    - Subspace identification.
    - Band selection.

Subspace identification

- Rare signal preservation:
  - Second-order statistics based methods such as PCA, MNF and SVD have proven not to be suitable for hyperspectral data.
  - Hyperspectral images contain many subtle materials with subpixel sizes that are missed by second-order statistics.
  - Some novel DR methods try to preserve rare signals combining second-order-statistics with techniques based on the l_2^∞ norm, dividing the subspace in two: the signal subspace and the rare vector subspace.
- Use of manifolds and tensors:
  - Improvements to the ISOMAP method to find the nonlinear structure of hyperspectral data.
  - Use of tensors to jointly process spatial and spectral information for denoising and DR.

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Subspace identification

- Use of a-priori information about the data, in the form of partial labeling.
  - Looking for the subspace that minimizes a discriminative term that assesses the pairwise class separability of the labeled data samplesand a regularization term that characterizes some property of the original data space (variance).
  - Pursue both DR and classification in a row by pruning a neural network input layer.
  - Project labeled samples onto a new 'prototype space' defined by the bands and cluster projected data in order to perform DR by grouping bands containing similar information.
  - Improvements to extensions of Fisher's linear discriminant analysis (LDA) to reduce the dimensionality and increase the classification accuracy.

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Band selection

- Model the hyperspectral DR as a band selection problem where subsets of the original bands are selected and averaged to form a spectral band.
- Use of labeled samples:
  - Modify a well-know algorithm for target detection, the constrained energy minimization (CEM) algorithm, to linearly constrain a band image while minimizing band correlation or dependence provided by other band images.
  - Evaluate labeled sample data statistical dependence by the so-called Hilbert-Schmidt independence criterion (HSIC). Then, the proposed method looks for those bands that minimize the associated HSIC p-value.

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  - A method based on the canonical correlation feature selection (CCFS) algorithm to find optimal superpositions of the spectral bands representing the most informative directions in the sensor space for specific patterns in the presence of noise.
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Spectral unmixing

- Spectral unmixing (SU) is a common technique in hyperspectral analysis.
- In SU the hyperspectral image can be seen as a linear/non-linear mixture of:
  - The spectral signatures of the materials in the image (endmembers).
  - Their fractional spatial distributions (abundances).
  - Additive noise.

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- SU requires to know the endmembers of the materials in the image, information that is rarely known a-priori.
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Endmember induction

- Recent works present new geometrical simplex-based methods or improvements to the existing ones dealing with highly mixed data, uniform/nonuniform additive Gaussian noise, real time requirements or the presence of anomalous materials.
- Lattice computing is an alternative to geometrical simplex formulation, where a connection between linear mixing model algebraic properties and lattice independence is established.
- Non-negative matrix factorization (NMF) is another alternative technique that exploits the positive matrix representation of hyperspectral linear mixing model.
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Non-linear Spectral Unmixing

- Non-linear spectral unmixing (NLSU) has attracted increasing attention in the last years.
  - Kernelization of LSU methods allows to estimate non-linear abundances.
  - The generalized bilinear model (GBM) is a model for non-linear unmixing of hyperspectral data due to multipath effects.
  - Use of labeled data samples to estimate the non-linear abundances of given endmembers through Gaussian synapse artificial neural networks.
  - An algorithm based upon simplex volume maximization, that uses shortest-path distances in a nearest-neighbor graph in spectral space, hereby respecting the nontrivial geometry of the data manifold in the case of nonlinearly mixed pixels.

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Hybrid Spectral Unmixing approaches

- Some recent methods follow a hybrid approach where endmember induction and spectral unmixing define an optimization problem.
  - Genetic algorithms, swarm techniques, Bayesian formulations.
- Combine endmember induction and linear unmixing techniques to address content-based image retrieval for large hyperspectral databases.
- Allow spectral unmixing to be performed directly on compressed data without any need to reconstruct hyperspectral imagery prior to analysis.

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Thank you!

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- Contact data:
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