Hyperspectral Imaging: An Emerging Technique in Remote Sensing

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Hyperspectral Image Spectrometry Concept

Each spatial element has a continuous spectrum that is used to analyze the surface and atmosphere.

224 spectral images taken simultaneously.
Hyperspectral Image Spectrometry Concept
Multispectral

Hyperspectral

Pixel Has Discrete Spectral Bands

Pixel Has Contiguous Spectrum

R

Wavelength (μm)

R

Wavelength (μm)
Hyperspectral Pixel Vector
Hyperspectral Data Cube
AVIRIS and HYDICE images of Cuprite NV with sizes 10 km x 15 km and 1 km x 1 km. Both images are three-color composites of selected individual bands in the visible range.
Unique Features of Hyperspectral Imagery

- High spectral resolution (10 nm <)
- High spatial resolution
- Extract subtle material substances for detection, discrimination, classification, quantification and identification
- Uncover unknown signal sources that cannot be identified *a priori*
- Interference more dominant than noise
Characterization of Hyperspectral Images

- **Non-literal Analysis**
  - Spectral properties resulting from different spectral wavelengths

- **Subpixel and mixed pixel analysis**
  - Low spatial and low spectral resolution
Functional Taxonomy

classification

quantification

identification

discrimination

detection
DoD Applications

- Targets are relatively small and usually can be embedded in a single pixel or occupy only a few pixels
- Targets occur with low probabilities
- Targets are generally insignificant in terms of 2nd order of statistics
- Image background is unknown
- No *a priori* information available
Other Applications

- Rare minerals in geology
- Special spices with a small population in agriculture, ecology
- Small transportation in law enforcement such as fast small boats for smuggling and drug trafficking
- Small targets in a large battlefield
- Toxic waste in environmental monitoring
- Chemical/biological agent detection
- Magnetic resonance imaging (MRI)
Motivations

- Due to high spatial and spectral resolution, hyperspectral sensors can now uncover many material substances which cannot be resolved by multispectral sensors. These signal sources may include unknown natural or background signatures, unidentified interferers.

- Many multispectral image classification techniques may not be effective for hyperspectral imagery.
In many applications, the targets are of major interest rather than pattern classes.

Gaussian noise assumption is generally not true in remotely sensed imagery. In this case, maximum likelihood approach is not applied.
Pigeon Hole Principle

- If a number of pigeons greater than a number of nests (i.e., pigeon holes), there is at least one pigeon hole which must accommodate at least two or more pigeons.

- Bands = pigeon holes

- Target sources = pigeons

- Use a band to detect, discriminate, classify or identify a particular target source.
Four issues needed to be addressed

- Number of bands, $L$ must be greater than or equal to the number of target sources, $p$, i.e., $L > p-1$.
  - Solution: Hyperspectral imagery seems to satisfy this condition.

- Once one band is used to accommodate a target source, it cannot be used again.
  - Solution: Orthogonal Subspace Projection (OSP)
Four issues needed to be addressed (Cont’d)

- How to determine number of target sources, $p$, in hyperspectral data
  - Solution: Virtual dimensionality (VD)
- Once $p$ is determined, how to find the $p$ target sources.
  - Solution: design and develop unsupervised target finding algorithms
Hyperspectral Imagery versus Multispectral Imagery

- Using the linear mixture model as a means of differentiating hyperspectral imagery from multispectral imagery
  - If $L \geq p$, the system solving the mixing problem is over-determined in which case the image is hyperspectral
  - If $L < p$, then the system solving the mixing problem is under-determined in which case the image is multispectral.
Hyperspectral Data Exploitation

- **Dimensionality Reduction**
- **Band Selection**
- **Endmember extraction**
  - An endmember is a pure and idealized signature to specify a spectral class
- **Anomaly Detection**
- **Target Detection**
  - Subtarget Detection
  - Unsupervised Target Detection
Hyperspectral Data Exploitation (Cont’d)

- Mixed Pixel Analysis
  - Classification
  - Quantification
  - Identification

- Exploitation-based Data Compression

- Signature Coding

- Signature Characterization

- Real-Time Implementation
Dimensionality Reduction

- **Component Analyses**
  - Principal Components Analysis
  - High Order Statistics-based Component Analysis
  - Independent Component Analysis

- **Projection Pursuit**

- **Feature Space-based Transforms**
  - OSP
  - Fisher’s Linear Discriminant Analysis (FLDA)
Band Selection

- Uniform Band Selection
- Statistics-based Band Selection
  - $2^{\text{nd}}$ order statistics
  - High order statistics (skewness, kurtosis, etc.)
  - Projection index
- Constrained Band Selection
  - CEM
  - Linearly Constrained Minimum Variance (LCMV)
Endmember Extraction

- Orthogonal Projection
  - Pixel Purity Index (PPI)
  - Vertex Component Analysis (VCA)
  - Automatic Target Generation Process (ATGP)
- Minimum/Maximum Simplex Volume
  - Minimum Volume Transform (MVT)
  - N-FINDR algorithm
  - Convex Cone Analysis (CCA)
  - Simplex Growing Algorithm
Endmember Extraction (Cont’d)

- **Least Squares Error**
  - Unsupervised Fully Constrained Least Squares
  - Unsupervised Non-negativity Constrained Least Squares

- **Statistics-based Component Analyses**
  - $2^{nd}$ order statistics
  - High order statistics ($3^{rd}$, $4^{th}$, $k^{th}$ order statistics)
  - Independent Component Analysis (ICA)
Hyperspectral Data Exploitation (Cont’d)

Anomalies or endmembers?

200x200 image size

64x64 image size

RX detector operating on TI3
Anomaly Detection

- RXD-type Detectors
  - Low Probability Detector (LPD)
  - Dual Window Eigen Separation Transform (DWEST)
- Multiple Window Anomaly Detection
  - Nested Spatial Window Target Detection (NSWTD)
  - Multiple Window RXD-type Detectors
Mixed Pixel Analysis

Classification
- Linear Spectral Unmixing
  - Abundance-unconstrained: OSP
  - Partially Abundance Constrained: SCLS, NCLS
  - Fully Abundance Constrained: FCLS

Quantification
- FCLS

Identification
- SAM (Spectral Angle Mapper)
- SID (Spectral Information Divergence)
Classical Approach: Linear Spectral Mixture Model

\[ \mathbf{r} = \mathbf{M}\alpha + \mathbf{n} \]

where

- \( \mathbf{r} = \begin{pmatrix} r_1 & r_2 & \cdots & r_L \end{pmatrix}^T \) L×1 acquired pixel vector
- \( \mathbf{M} = \begin{bmatrix} \mathbf{m}_1 & \mathbf{m}_2 & \cdots & \mathbf{m}_p \end{bmatrix}^T \) endmember signature matrix which can be known or unknown
- \( \alpha = \begin{pmatrix} \alpha_1 & \alpha_2 & \cdots & \alpha_p \end{pmatrix}^T \) abundance vector
- \( \mathbf{n} = \begin{pmatrix} n_1 & n_2 & \cdots & n_L \end{pmatrix}^T \) random noise vector
- The source \( \alpha \) is unobservable
Detect the desired targets by eliminating undesired signals $U$ followed by a match filter specified by the desired signature, $d$. That is, we re-express the linear mixing model by $r = γU + α_d d$

$$P_{OSP} r = M_d P_{⊥} U r = d^T P_{⊥} U r$$

where $P_{⊥} U = I - U(U^T U)^{-1} U^T$ is the undesired signature annihilator

$M_d x = d^T x$ is a matched filter with the matched signature specified by $d$
Target Detection

- **Supervised Target Detection**
  - Complete Knowledge Linear Spectral Unmixing
    - OSP
  - Partial knowledge Subtarget Detection: CEM

- **Unsupervised Target Detection**
  - Unsupervised Lienar Spectral Unmixing
  - Unsupervised Subtarget Detection
Exploitation–based Data Compression

- **Lossless Compression**
  - JPEG 2000
  - SPIHT (Set Partition in Hierarchical Tree)

- **Lossy Compression**
  - Spectral Compression
    - Dimensionality Prioritization
    - Band Prioritization
  - Spatial Compression
  - Joint Spectral/Spatial Compression
Hyperspectral Signature Coding

- Memoryless Signature Coding
  - Binary Coding
    - SPAM (Spectral Program Analysis Manager)
    - SBFC (Spectral Binary Feature Coding)

- Memory Signature Coding
  - Texture-based SFDC (Spectral Derivative Feature Coding)
  - Arithmetic Coding-Based SPFC (Spectral Probabilistic Feature Coding)

- Progressive Signature Coding
Hyperspectral Signature Characterization

- Kalman Filtering for Hyperspectral Signature Feature Characterization
- Band Selection for Hyperspectral Signature Feature Characterization
- Wavelet-based Techniques for Hyperspectral Signature Feature Characterization
AVIRIS Data

- AVIRIS (Airborne Visible/InfraRed Imaging Spectrometer) Lunar Crater Volcanic Field, Nevada
  - 5 targets of interest: cinders, playa, rhyolite, shade and vegetation.
  - A two-pixel anomaly located at the upper edge of the dry lake
HYDICE Data

HYDICE (Hyperspectral Digital Imagery Collection Experiment) spectral: 10nm and spatial: 1.56m

- 15 panels made from five different materials
- They are arranged into a matrix in such a way that each row represents 3 panels of the same type with three different sizes, 3mx3m, 2mx2m, 1mx1m. Each column represents 5 panels of different types with the same size.

Original image

Target masked image
References

- **Web Site**
  - [www.umbc.edu/rssipl](http://www.umbc.edu/rssipl)

Hyperspectral Imaging
Techniques for Spectral Detection and Classification
Chein-I Chang
(157 citations)
Experience in Publications (Cont’d)

- Three Edited Books

Hyperspectral Data Exploitation

Theory and Applications

editted by
Chein-I Chang

The rapid growth of interest in the use of hyperspectral imaging as a powerful remote sensing technique has been accompanied by hundreds of articles published in journals and conference proceedings. While new findings and applications dispelled across numerous sectors, this contributed work provides a much-needed synthesis of what is known, what can be expected from current research and development, and what new research is needed.

The book’s eleven chapters represent some of the field’s most important innovations and advances from around the world. Each begins with an overview written by the editor that discusses the design of imaging sensors and the development of hyperspectral imaging techniques. This overview also provides a brief introduction to each of the book’s thirteen chapters, with an emphasis on the connections among them. Chapters are organized into three parts: Theory, Theory, and Applications.

Among the topics covered are: preprocessing, image processing, data visualization, data representation, and detection and estimation, classification, data compression, and data transmission algorithms. Readers discover a wide range of current and emerging techniques for surface material identification, evaluation, and analysis of materials. Many of the chapters feature case studies that demonstrate applications in defense and homeland security, intelligence, environmental sciences, geology, and agriculture.

Researchers and practitioners throughout the field of remote sensing will find this volume an exceptionally valuable reference that brings together, analyzes, and synthesizes the many research findings and emerging applications in hyperspectral imaging.

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New Book to be Published

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Questions?
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