CBIR for hyperspectral images

Miguel A. Veganzones

Grupo Inteligencia Computacional
Universidad del País Vasco

Outline

1. Introduction
   - Hyperspectral images
   - CBIR systems
2. Feature Characterization
   - Endmember induction and unmixing
   - Information quantification
3. CBIR system for hyperspectral images
   - Queries
   - Retrieval
4. Experiment
   - Design
   - Results
   - Conclussions

Outline

AVIRIS cube

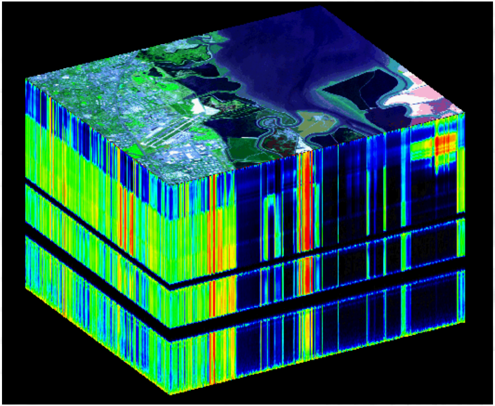
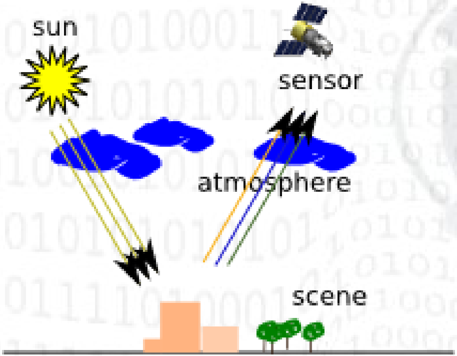


Figure: Imagen tomada desde el JPL's Airborne Visible/Infrared Imaging Spectrometer volando a 20.000 metros sobre Moffett Field, California.

Hiperespectrales VS Multiespectrales

- Número de bandas:
  - Color/Multiespectrales: 3-10 bandas.
  - Hiperespectrales: >100.
- Resolución espectral: longitud de onda/ancho de banda
  - Color/Multiespectrales: orden de 10.
  - Hiperespectrales: orden de 100.
- Contigüidad:
  - Color/Multiespectrales: muestreos irregulares del espectro.
  - Hiperespectrales: muestreos regulares del espectro.

Sistemas de imagen hiperespectrales

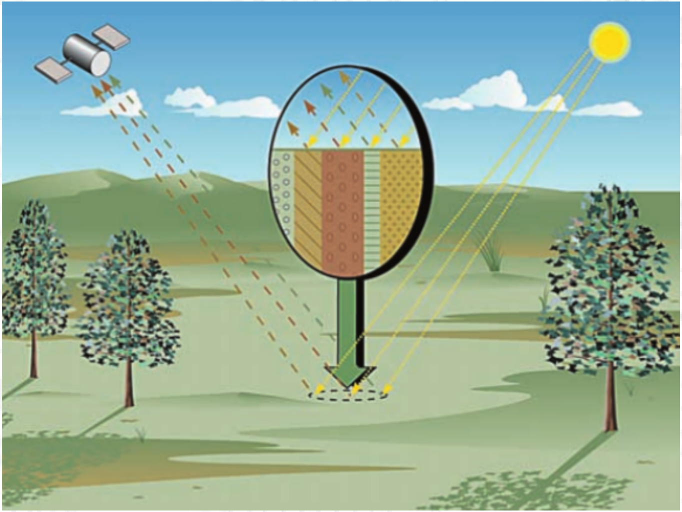


Información espacial/espectral

- Información espacial:
  - Cada pixel representa un espacio determinado de la escena.
  - Depende de la altitud y apertura del sensor.
- Información espectral:
  - Se obtiene mediante un interferómetro o prisma.
  - Un conversor convierte la radiancia muestreada en cada señal espectral.

Modelo de mezcla lineal

Ilustración



Modelo de mezcla lineal

Formulación

LMM

- $H = A \cdot E + \eta$
- $\mathbf{h}(\mathbf{x},\mathbf{y}) = a(x,y)_1 \cdot \mathbf{e_1} + a(x,y)_2 \cdot \mathbf{e_2} + \ldots + a(x,y)_p \cdot \mathbf{e_p} + \eta$

donde:

- H es una imagen hiperespectral con dimensiones espaciales $m \times n$ y con d bandas espectrales.
- A es una imagen de abundancias espectrales con dimensiones espaciales $m \times n$.
- E es un conjunto de p firmas espectrales (endmembers) con d bandas.
- η es ruido aditivo.

Modelo de mezcla lineal

Restricciones

LMM

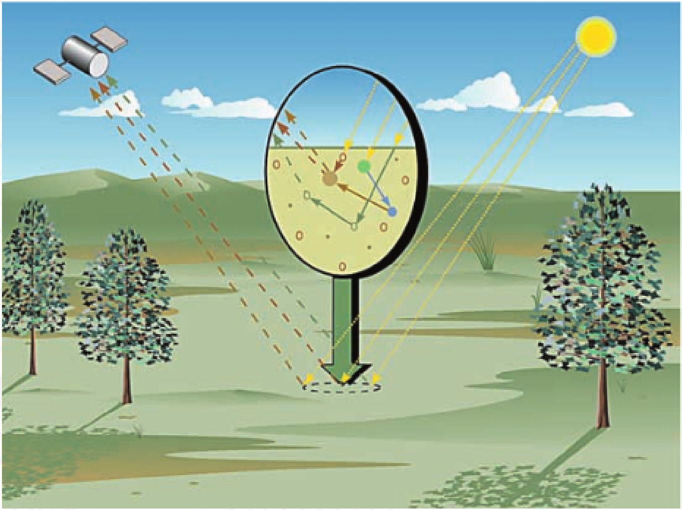
- $H = A \cdot E + \eta$
- $\mathbf{h}(\mathbf{x},\mathbf{y}) = a(x,y)_1 \cdot \mathbf{e_1} + a(x,y)_2 \cdot \mathbf{e_2} + \ldots + a(x,y)_p \cdot \mathbf{e_p} + \eta$

sujeto a:

- Abundance Non-negative Constraint (ANC): $a(x,y)_i \geq 0$
- Abundance Sum-to-one Constraint (ASC): $\sum_i a(x,y)_i = 1$

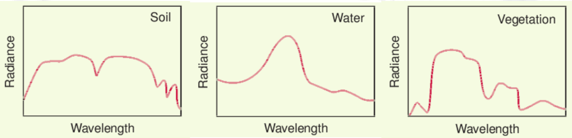
Modelo de mezcla no lineal

Ilustración



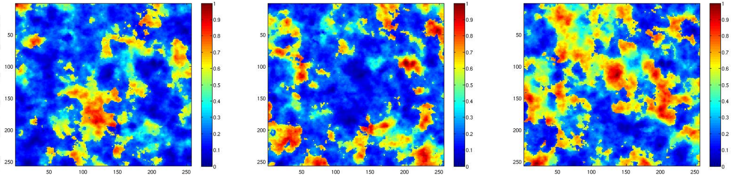
Endmembers

- Firmas espectrales de distintos materiales a una escala, resolución y frecuencias dadas.
- USGS library: firmas espectrales de multitud de materiales obtenidas mediante técnicas de espectroscopía con microscopios en laboratorio.



Imágenes de abundancia

- Indican la proporción de cada material en la imagen.
- Información espacial.



Demezclado (Unmixing)

- Obtener las imágenes de abundancia a partir de la imagen hiperespectral original y un conjunto de firmas espectrales (endmembers).
- Estimación mediante mínimos cuadrados (Least-Squares Estimation).

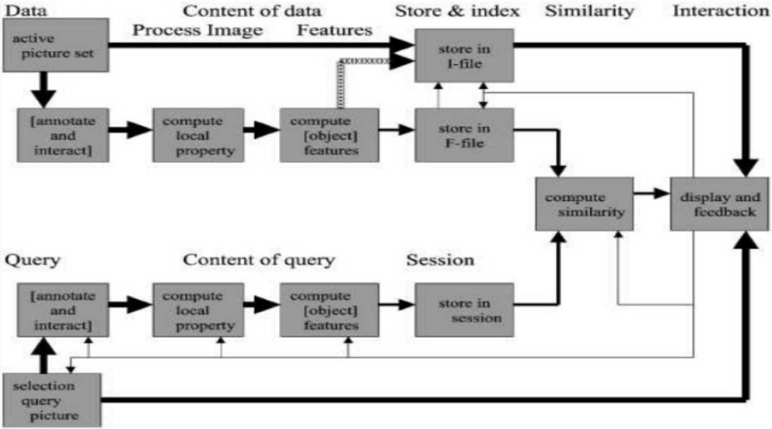
Outline

1. Introduction
   - Hyperspectral images
   - CBIR systems
2. Feature Characterization
   - Endmember induction and unmixing
   - Information quantification
3. CBIR system for hyperspectral images
   - Queries
   - Retrieval
4. Experiment
   - Design
   - Results
   - Conclussions

Objetivos

- Recuperar información de grandes bases de datos (imágenes).
- Superar las deficiencias de los métodos tradicionales basados en metadatos.
- Usar la información contenida en las imágenes como base para las búsquedas.
- Elaboración de métricas basadas en la caracterización de la información contenida en las imágenes.

Descripción



* From "Content-Based Image Retrieval at the end of the early years". W.M.Smeulder et al. IEEE Trans. on Pattern Analysis and Machine Intelligence (2000)

Retrieval feedback

- Salto semántico: existe una brecha entre la información semántica buscada por el usuario y la caracterización de la información de las imágenes.
- Especialmente importante en dominios amplios (variabilidad del catálogo de imágenes).
- Retrieval feedback: proceso iterativo por el cual el usuario refina la búsqueda en función de los resultados previos (selección de resultados positivos y negativos).

Outline

Endmember induction

- Induce the set of endmember that form the hyperspectral image.
- It must be an automatic and, desirablely, a fast process.
- Different methodologies: geometrical, heuristics, morphological, ...
- More or less, they all follow the linear mixing model.

Unmixing

- Extract the abundancies of each endmember in the hyperspectral image.
- Different methods depending on the restrictions to the model and the provided information about the endmembers.

Outline

1. Introduction
   - Hyperspectral images
   - CBIR systems
2. Feature Characterization
   - Endmember induction and unmixing
   - Information quantification
3. CBIR system for hyperspectral images
   - Queries
   - Retrieval
4. Experiment
   - Design
   - Results
   - Conclussions

Feature vector

- The feature vector describing an hyperspectral image is defined by:
  - A set of endmembers.
  - A probability of ocurrence of each endmember.
  - The abundance images of eeach endmember.
- The number of features for each image is variable: each image has a different number of endmembers.

Methodologie

- Endmember induction:
    - Virtual dimensionality methods: helps to tune the induction method.
    - Morphological methods: fasts and automatic.
- Abundance extraction:
    - Least Squares method.
    - Full-Constarined Least Squares method.
- Modelling ocurrence and spatial information:
    - Statistics: mean, variance, kurtosis, ...
    - Markov Random Fields.

Outline

Spectral queries

- Images containing a set of specific endmembers: $Q = \{\bigcup_{i=1}^{n} E_i\}$.
- Images containing a set of specific endmembers and not containing a distinct set of specific endmembers: $Q = \{\bigcup_{i=1}^{n} E_i\} \wedge \neg \{\bigcup_{j=1}^{m} E_j\}$, where $E_i \neq E_j, \forall i, j$.

Spectral/Spatial queries

- Images containing a set of specific endmembers whose ocurrence is given by a probability distribution function: $Q = \{\bigcup_{i=1}^{n} F(E_i)\}$.
- Images containing a set of specific endmembers with a determined spatial distribution: $Q = \{\bigcup_{i=1}^{n} (E_i \wedge A_i)\}$.

Outline

System definition

- The user defines the query.
- The system characterizes the set of images: endmembers and abundancies (independently denoted as samples).
- The system compares the query characteristics with the characteristics of the database images and establish a similarity ordered list, S.
- The system presents to the user the $k > 0$ first images of S, denoted by S_k.
- The user redefines the query by adding relevance information in S_k.

Only positive samples

- When the query is defined only as a set of positive samples.
- Model the positive class and retrieve the images with higher probability of being an ocurrence of the modelled class.
- Kernel One-Class Support Vector Machine (KOC-SVM) [5].

Positive and negative samples

- The query is defined as a set of positive and negative samples.
- The positive samples form a well defined class.
- The negative samples form a very heterogeneous group that cannot be modelled as a class but it gives usable information.
- Alternatives:
    - Classic two-classes SVM.
    - One-class SVM /SVDD for both positive/negative classes [5, 6].

Only negative samples

- The query is defined only as a set of negative samples.
- The desired class cannot be modelled but negative samples can be used to restrict the search.
- One-class SVM / SVDD for negative samples [6].

With ocurrence probability

- The query is defined by a set of positive and/or negative samples and an associated probability distribution function for each.
- Each endmember has associated a probability of ocurrence.
- Alternatives:
  - Modifications of the previous methodologies.
  - Weighted kernel density estimations.

With spatial distribution

- The query is defined by a set of positive / negative samples and abundance images associated to them.
- Each endmember has associated an abundance image.
- Alternatives:
  - Modifications of previous methodologies.
  - Model the spatial information indepentdenly (MRF).

Outline

Outline

Outline

For Further Reading I

- Hyperspectral Data Explotation: Theory and Applications. Chein-I Chang. 2007.
- Hyperspectral Imaging: Techniques for Spectral detection and Classification. Chein-I Chang. 2003.
- Signal Theory Methods in Multispectral Remote Sensing. David A. Landgrebe. 2003.
- Remote Sensing: the Image Approach, 2nd Edition. John R. Scott. 2007.
- One-Class SVM for Learning in Image Retrieval. Yunqiang Chen, Xiang Zhou, Thomas S. Huang. Proc. IEEE Int. Conf. on Image Processing, Thessaloniki, Greece. 2001.

For Further Reading II

Non-Relevance Feedback Document Retrieval Based on One-Class SVM and SVDD. Takashi Onoda, Hiroshi Murata, Seiji Yamada. International Joint Conference on Neural Networks, Vancouver, Canada. 2006.

Questions?

Thank you very much for your attention.

- Contact:
  - Miguel Angel Veganzones
  - Grupo Inteligencia Computacional
  - Universidad del País Vasco - UPV/EHU (Spain)
  - E-mail: miguelangel.veganzones@ehu.es
  - Web page: http://www.ehu.es/computationalintelligence