Validation of a Hyperspectral Content-Based Information Retrieval (RS-CBIR) System upon scarce data

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Outline

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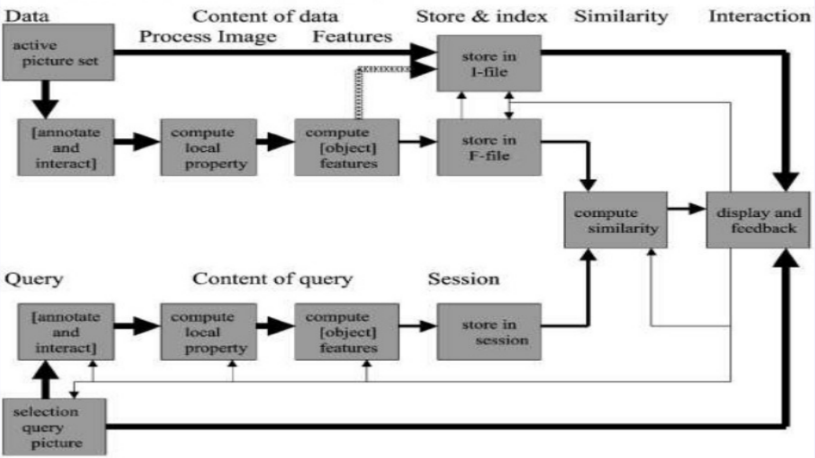
CBIR systems

- Recover image/multimedia information from large databases using the own images content.
- Solve traditional metadata-based problems.
- Information characterized by low level features (color, textures, shape, ...).
- Compare image dissimilarities by distance functions computed over the features.
- Improve searches by user interaction (Retrieval feedback, Active Learning).

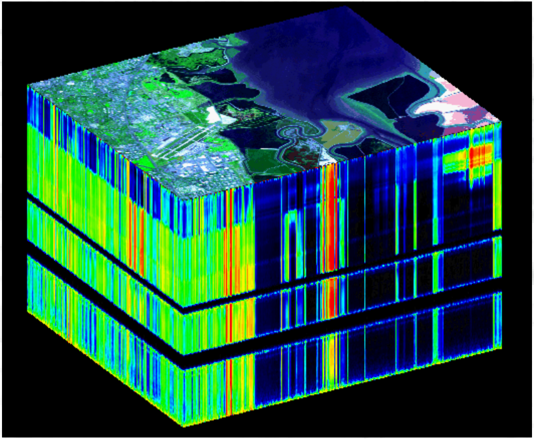
Diagram



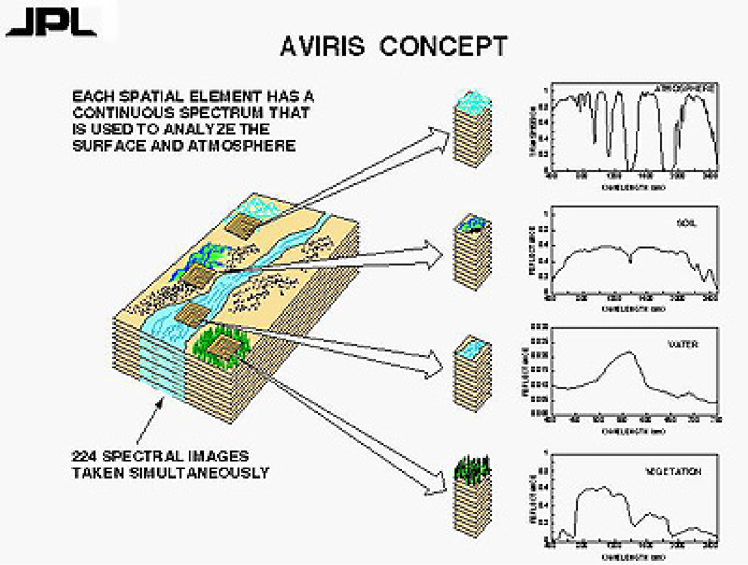
* From "Content-Based Image Retrieval at the end of the early years". W.M.Smeulder et al. IEEE Trans. on Pattern Analysis and Machine Intelligence (2000)

Outline

Hyperspectral cube



Hyperspectral remote sensing



Color/multispectral - Hyperspectral differences

- Bands:
  - Color/Multispectral: 3-10 bands.
  - Hyperspectral: >100.
- Spectral resolution (wavelength/bandwidth):
  - Color/Multispectral: order 10 (low).
  - Hyperspectral: order 100 (high).
- Contiguity:
  - Color/Multispectral: irregular / overlapping.
  - Hyperspectral: regular / non-overlapping.

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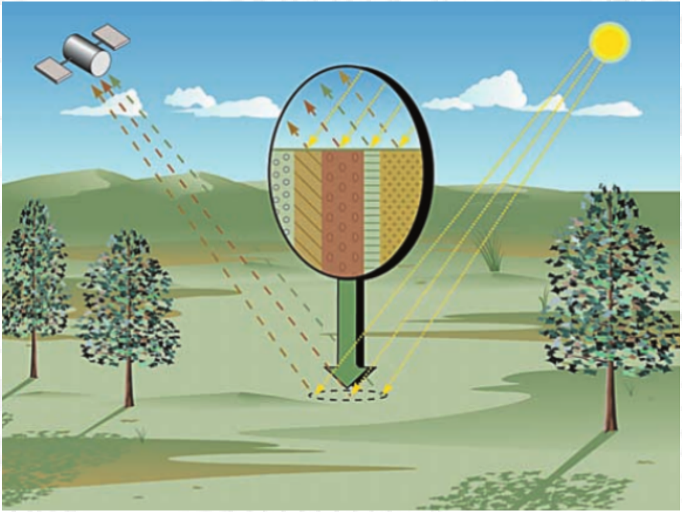
Linear Mixing Model

Illustration



Linear Mixing Model
Formulation

LMM

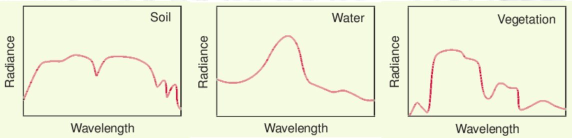
- $H = A \cdot E + \eta$
- $\mathbf{h}(\mathbf{x},\mathbf{y}) = a(x,y)_1 \cdot \mathbf{e_1} + a(x,y)_2 \cdot \mathbf{e_2} + \ldots + a(x,y)_p \cdot \mathbf{e_p} + \eta$

where:

- H is an hyperspectral image.
- E is a set with the materials spectral signs (endmembers): spectral information.
- A is a set of fractional abundances images, one for each endmember: spatial information.
- η is additive noise.

Endmembers induction

- Find by automatic unsupervised methods the spectral signs (endmembers) of the material on the image.



- Each hyperspectral image H_α is characterized by its induced set of endmembers $E_\alpha = \{\mathbf{e}_1, \ldots, \mathbf{e}_{p_\alpha}\}$, where p_α is the number of induced endmembers from α-th image.

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Diagram

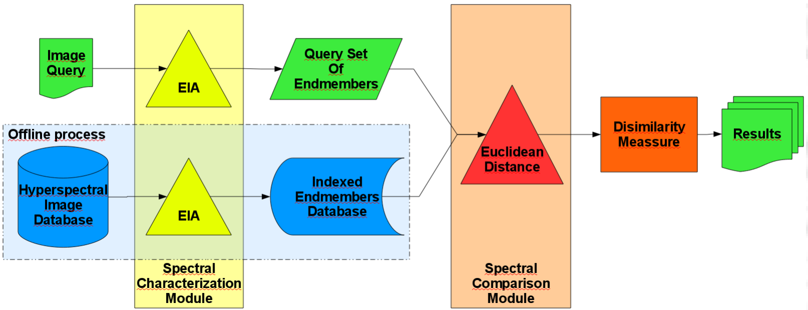
Image Query
EIA
Query Set Of Endmembers
Offline process
Hyperspectral Image Database
EIA
Indexed Endmembers Database
Spectral Characterization Module
Euclidean Distance
Spectral Comparison Module
Disimilarity Meassure
Results

Spectral distances

- The matrix of distances between two sets of endmembers E_α and E_β is given by

$$D = \left\{ d_{ij} \right\}; i = 1, \ldots, p_\alpha; j = 1, \ldots, p_\beta$$

where d_{ij} can be, for instance, the Euclidean distance, d_{euc}, or the angular distance, a.k.a. Spectral Angle Mapper, d_{sam}:

$$d_{euc}\left(\mathbf{e_1}, \mathbf{e_2}\right) = \sqrt{\sum_{\lambda=1}^{q} \left(e_1^\lambda - e_2^\lambda\right)^2}$$

$$d_{sam}\left(\mathbf{e_i}, \mathbf{e_j}\right) = \cos^{-1}\left(\frac{\sum_{\lambda=1}^{q}\left(e_i^\lambda e_j^\lambda\right)}{\sqrt{\sum_{\lambda=1}^{q}\left(e_i^\lambda\right)^2}\sqrt{\sum_{\lambda=1}^{q}\left(e_j^\lambda\right)^2}}\right)$$

Spectral dissimilarity

- Compare two hyperspectral images H_α, H_β by theirs spectral features:

$$s\left(H_\alpha, H_\beta\right) \equiv s\left(E_\alpha, E_\beta\right) = \left(m_r + m_c\right)\left(\left|p_\alpha - p_\beta\right| + 1\right)$$

where m_r and m_c are the mean of the vectors of minimal values of the distance matrix, D, computed by rows and columns respectively.

Outline

Evaluation metrics

- The two most used evaluation measures are *precision* and *recall*.
  - Precision, p, is the fraction of the retrieved images that are relevant to the query.
  - Recall, q , is the fraction of retrieved relevant images respect to the total number of relevant images in the database according to a priori knowledge.
- If we denote T the set of returned images and R the set of all the images relevant to the query, then

$$p = \frac{|T \cap R|}{|T|} \qquad q = \frac{|T \cap R|}{|R|}$$

- Results are usually summarized as precision-recall or precision-scope curves.

Problems

- Lack of ground truth knowledge (predefined categories):
    - Due to the expensive, tedious and error prone ground truth gathering process.
    - Well known problem in RS classification.
- Users difficulties to evaluate the retrieved images giving a positive/negative feedback:
    - Specific problem of CBIR systems in a Remote Sensing context.
    - RS images are not easily interpreted by visual inspection.
    - RS-CBIR feedback retrieval requires domain-specific skills and new interaction methodologies yet to be developed.

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Proposed strategy

- Use the RS data inherent structures to simulate potential users queries.
- We propose to build the groundtruth of a potential query by a clustering process.
- Thus, the groundtruth modeled by a clustering process is a relevant set $R(q_i) = \{x_{i_1,}, \ldots, x_{i_k,}\}$ where $q_i = \{x_i\}$ is the query, and images $\{x_{i_1,}, \ldots, x_{i_k,}\}$ belong to the same cluster than x_i.
- The set of all the queries, $Q = \{q_i\}_{i=1}^n$, represents a simulated family of queries whose groundtruth is given by a clustering process.

Hyperspectral CBIR validation

- Precision and recall quality measures can be given using the proposed relevant set $R(q_i) = \{x_{i_1}, \ldots, x_{i_k},\}$.
- The ideal response of a CBIR system M to a potential query q_i is a ranked list given by

$$f_M(q_i) = \left\{x_{i'_1}, \ldots, x_{i'_k}, x_{i'_{k+1}}, \ldots, x_{i'_n}\right\}$$

where $\left\{x_{i'_1}, \ldots, x_{i'_k},\right\}$ is any permutation of the images belonging to the relevant set $R(q_i)$.

Hyperspectral database

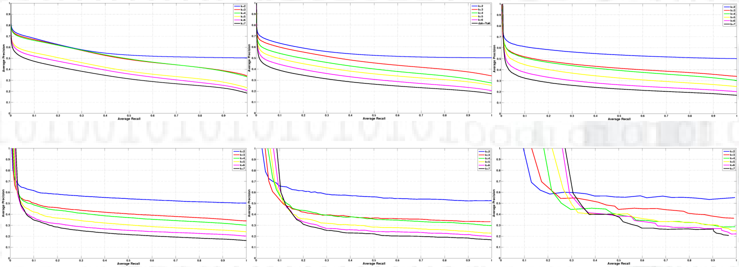
- We applied the Hyperspectral CBIR over a scene provided by HyVista Corp. and DLRs optical Airborne Remote Sensing and Calibration Facility service.
- The scene is a big image of 2878 $\times$ 512 pixels and 125 spectral bands.
  - Twelve bands corresponding to water absorption bands have been removed, remaining 113 bands.
- The image has been captured over the DLR facilities in Oberpfaffenhofen (Germany), and consist mainly of vegetation and fields, in addition to the DLR facilities and some small towns buildings.
- We built six datasets by cutting the scene in patches of increasing sizes, from 8 $\times$ 8 pixels (23040 patches) up to 256 $\times$ 256 pixels (24 patches).

Potential queries simulation

- For each dataset we performed several clusterings on the average radiance of each patch sample by means of the ELGB clustering algorithm.
  - Different values of the number of clusters, $k = 2, \ldots, 7$.
  - The ELGB is an enhanced k-means clustering algorithm which has a strong robustness against initial condition variations.
- For each dataset and cluster, the mean and standard deviation were calculated in order to purge those patches away from two times the standard deviation.
  - Eliminating ambiguous samples.
- Each clustering is assumed to be the ground truth of the expected response to a simulated family of queries, against which the RS-CBIR must compete.

Results

- Precision/recall curves for the different datasets:



- Decrease on the performance of the Hyperspectral CBIR system as the diversity of the simulated queries, given by the number of clusters k, increases.
- The size of the images does not affect significantly the performance of the Hyperspectral CBIR system.

Summary

- There is a big need of new strategies to validate RS-CBIR systems that could successfully overcome the lack of ground truth data.
- We have developed a methodology for RS-CBIR systems quality assessment, inspired in the DAMA strategy for unsupervised segmentation quality assessment in remote sensing images.
  - Our methodology works when little or no ground truth data are available.
- We show an example of its applicability to test a Hyperspectral CBIR system.

Thanks

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