ON THE VALIDATION OF A SPECTRAL/SPATIAL CBIR SYSTEM FOR HYPERSPECTRAL IMAGES

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Outline

CBIR systems

- Images indexed by feature vectors extracted by means of computer vision and digital image processing techniques.
- The interrogation to the database is done through the presentation of a query image.
- The answer are the most similar images in the database according to some similarity measure.

Remote Sensing CBIR systems

- Motivation: huge amount of Earth Observation data provided by remote sensors.
- Approaches to CBIR in remote sensing images proposed up to now are focused on panchromatic, SAR or low dimension multispectral images.
- CBIR techniques has not been properly addressed for the case of hyperspectral images.

Hyperspectral CBIR systems

- Few works in the literature.
- Image features as the endmembers induced by some Endmembers Induction Algorithm (EIA).
- Inconvenient: they can not discriminate among images with the same induced endmembers but very different spatial distributions.
- We propose an Spectral-Spatial CBIR system for hyperspectral databases.

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CBIR systems validation

- Most frequently used evaluation measures:
  - Precision (p): fraction of the returned images that are relevant to the query.
  - Recall (q): fraction of returned relevant images respect to the total number of relevant images in the database.
- Implementation:
  - A-priori ground-truth knowledge (categories).
  - User's online evaluation.

Validation in Remote Sensing domain

- Handicaps:
  - Lack of ground-truth knowledge (categories).
  - Users have difficulties to evaluate the system's response.
- We validate the proposed Spectral-Spatial CBIR system using synthetic hyperspectral data.
  - We are working on CBIR systems validation without a-priori ground-truth knowledge.

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Linear Mixing Model

LMM

- $H = A \cdot E + \eta$
- $\mathbf{h}(\mathbf{x},\mathbf{y}) = a_1(x,y) \cdot \mathbf{e_1} + a_2(x,y) \cdot \mathbf{e_2} + \ldots + a_p(x,y) \cdot \mathbf{e_p} + \eta$

where:

- H is an hyperspectral image.
- E is the set of materials spectral signatures (endmembers): spectral information.
- A is the set of fractional abundance images: spatial information.
- η is additive noise.

Spectral/Spatial features

- We characterize an hyperspectral image H_α by a tuple $\langle E_\alpha, \Phi_\alpha \rangle$, where:
  - $E_\alpha = \left\{ \mathbf{e}_1^\alpha, \ldots, \mathbf{e}_{p_\alpha}^\alpha \right\}$ is the set of p_α induced endmembers.
  - $\Phi_\alpha = \left\{ \phi_1^\alpha, \ldots, \phi_{p_\alpha}^\alpha \right\}$ is the set of fractional abundance maps.
- An EIA is used to induce the spectral signatures (the endmembers) of the image.
- An unmixing method extracts from the image the fractional abundances of each endmember.

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Spectral/Spatial CBIR system

- Image similarity: similarity between image spectra and their relative abundance proportions.
- Spectral-Spatial dissimilarity: is a version of the Integrated Region Matching (IRM) dissimilarity function used for region matching-based image retrieval.
- Depends on two aspects:
  - The similarity between each region of the two images (spectral similarity).
  - The significance of each region matching (spatial similarity).

Spectral-Spatial dissimilarity function

- Given two images, H_α and H_β:
  1. We compute the Spectral Distance Matrix, $D_{\alpha,\beta}$:

  $$D_{\alpha,\beta} = [d_{ij}; i = 1, \ldots, p_\alpha; j = 1, \ldots, p_\beta]$$

  where d_{ij} is a distance between the endmembers $\mathbf{e}_i^\alpha$ and $\mathbf{e}_j^\beta$.
  2. Then, the Spectral-Spatial dissimilarity function, $s(H_\alpha, H_\beta)$, is defined as:

  $$s(H_\alpha, H_\beta) = \sum_{i,j} r_{ij} d_{ij}$$

  where r_{ij} is the significance associated to d_{ij}.

Significance matrix

- Thus, the problem reduces to choosing the significance matrix $R_{\alpha,\beta} = [r_{ij}; i = 1, \ldots, p_\alpha; j = 1, \ldots, p_\beta]$.
- We followed the most similar highest priority (MSHP) principle, making use of the average abundances $\bar{\Phi}_\alpha$ and $\bar{\Phi}_\beta$.
- The average abundances represent "significance credits" assigned to the spectral distances by IRM algorithm.

IRM algorithm

1. Set $\mathcal{L} = \{\}$ and denote $\mathcal{M} = \{(i,j) : i = 1,\ldots,p_\alpha; j = 1,\ldots,p_\beta\}$.
2. Choose the minimum d_{ij} for $(i,j) \in \mathcal{M} - \mathcal{L}$. Label the corresponding (i,j) as (i',j').
3. $r_{i'j'} = \min\left(\bar{\phi}^\alpha_{i'}, \bar{\phi}^\beta_{j'}\right)$.
4. If $\bar{\phi}^\alpha_{i'} < \bar{\phi}^\beta_{j'}$, set $r_{i'j} = 0$, $j \neq j'$; otherwise, set $r_{ij'} = 0$, $i \neq i'$.
5. If $\bar{\phi}^\alpha_{i'} < \bar{\phi}^\beta_{j'}$, set $\bar{\phi}^\alpha_{i'} = 0$ and $\bar{\phi}^\beta_{j'} = \bar{\phi}^\beta_{j'} - \bar{\phi}^\alpha_{i'}$; otherwise, set $\bar{\phi}^\beta_{j'} = 0$ and $\bar{\phi}^\alpha_{i'} = \bar{\phi}^\alpha_{i'} - \bar{\phi}^\beta_{j'}$.
6. $\mathcal{L} = \mathcal{L} + \{(i',j')\}$.
7. If $\sum_{i=1}^{p_\alpha} \bar{\phi}^\alpha_i > 0$ and $\sum_{j=1}^{p_\beta} \bar{\phi}^\beta_j > 0$, go to step 2; otherwise, stop.

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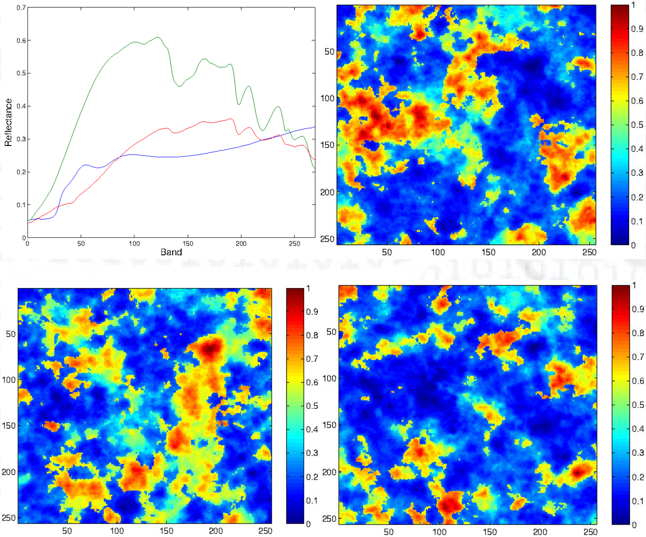
Synthesis procedure

- Generated as linear mixtures of a set of spectra (ground-truth endmembers) and synthesized abundance coefficients (ground-truth abundances).
  - Ground-truth endmembers: randomly selected from a subset of the USGS spectral library.
  - Ground-truth abundances: Gaussian Random Fields with Matern correlation function of parameters $\theta_1 = 10$ and $\theta_2 = 1$.
- We ensure that there are regions of almost pure endmembers and that the abundance coefficients sum up to one.

Synthesis example



Synthetic datasets

- 18000 hyperspectral images divided in nine datasets of 2000 images each.
- Each dataset is characterized by:
    - One of three pools of groundtruth endmembers, with 5, 10 and 20 endmembers each, representing an increasing diversity in the materials.
    - One of three spatial sizes, with images having 64×64, 128×128 and 256×256 pixels, representing different spatial scales.
- All the synthesized hyperspectral images have 269 spectral bands *per* pixel.
- Each image is built with 2 to 5 endmembers randomly selected from the corresponding pool of available groundtruth endmembers.

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Experiments

- We have performed independent experiments over each of the nine synthetic hyperspectral datasets using the proposed Spectral-Spatial dissimilarity function where:
    - The distance between endmembers is measured by the Euclidean distance, s_{euc}, and the Spectral Angle Map pseudo-distance, s_{sam}.
    - For each image, we apply independently the N-FINDER and the EIHA endmember induction algorithms to induce the set of endmembers.
- The abundances have been calculated by Full-Constrained Least Squares Unmixing (FCLSU).
- The Matlab code for the hyperspectral image synthesis and endmember induction is available from http://www.ehu.es/ccwintco/index.php/GIC-source-code-free-libre.

Experiment definition

- For each image H_α in a dataset we calculate the dissimilarity between H_α and each of the images in the dataset $(N = 2000)$:

$$\mathbf{s}_\alpha = [s_{\alpha 1}, \ldots, s_{\alpha N}]$$

where $s_{\alpha,\beta}$ is the dissimilarity between the images H_α and H_β.

- Let us distinguish between:
    - $\mathrm{s}_\alpha^{\mathrm{GT}}$: the vector of dissimilarities computed using the known ground-truth endmembers.
    - $\mathrm{s}_\alpha^{\mathrm{IND}}$: the vector of dissimilarities computed using the endmembers induced by one of the EIAs (either N-FINDER or EIHA).

Experiments ranking definition

- We sort the components of $\mathbf{s}_\alpha$ in increasing order, and the resulting shuffled image indices constitute the ranking:

$$\Omega_\alpha = \left[\omega_{\alpha,p} \in \{1,\ldots,N\}\,; p = 1,\ldots,N\right]$$

so that $s_{\alpha,\omega_{\alpha,p}} \leq s_{\alpha,\omega_{\alpha,p+1}}$.

- We distinguish rankings $\Omega_\alpha^{\mathrm{GT}}$ and $\Omega_\alpha^{\mathrm{IND}}$ corresponding to the ground-truth and induced dissimilarities, respectively.

Experiments query definition

- A query $Q_k(H_\alpha)$ is formulated as a search for the k most similar (less dissimilar) images H_β in the dataset with respect to the image H_α, with $1 \leq k \leq N$.
- The set of returned images $T_k(H_\alpha)$ and the set of relevant images $V_k(H_\alpha)$ for a query $Q_k(H_\alpha)$ are defined as follows:

$$T_k(H_\alpha) = \Omega^{\mathrm{IND}}_{\alpha,k} = \left[\omega^{\mathrm{IND}}_{\alpha,p} \text{ s.t. } s_{\alpha,\omega^{\mathrm{IND}}_{\alpha,p}} \leq s_{\alpha,\omega^{\mathrm{IND}}_{\alpha,k}}\right] \quad (1)$$

$$V_k(H_\alpha) = \Omega^{\mathrm{GT}}_{\alpha,k} = \left[\omega^{\mathrm{GT}}_{\alpha,p} \text{ s.t. } s_{\alpha,\omega^{\mathrm{GT}}_{\alpha,p}} \leq t\right] \quad (2)$$

where $t = \bar{s}^{\mathrm{GT}}_\alpha - 2\sigma_{\mathbf{s}^{\mathrm{GT}}_\alpha}$, and $\bar{s}^{\mathrm{GT}}_\alpha$ and $\sigma_{\mathbf{s}^{\mathrm{GT}}_\alpha}$ are respectively the mean and standard deviation of $\mathbf{s}^{\mathrm{GT}}_\alpha$.

Experiments quality meassures

- The Precision $P_k(H_\alpha)$ and Recall $R_k(H_\alpha)$ for a query $Q_k(H_\alpha)$ are defined as:

$$P_k(H_\alpha) = \frac{|V_k(H_\alpha) \cap T_k(H_\alpha)|}{|T_k(H_\alpha)|} \text{ and } R_k(H_\alpha) = \frac{|V_k(H_\alpha) \cap T_k(H_\alpha)|}{|V_k(H_\alpha)|}$$

- The Average Precision and Recall of the system for a query of size k are defined as:

$$P_k = \frac{1}{N} \sum_{\alpha=1}^{N} P_k(H_\alpha) \text{ and } R_k = \frac{1}{N} \sum_{\alpha=1}^{N} R_k(H_\alpha)$$

Experiments quality meassures II

- As summary performance quantity, we calculate the normalized average rank of relevant images:

$$Rank\left(H_{\alpha}\right) = \frac{1}{NN_{\alpha}}\left(\sum_{i=1}^{N_{\alpha}} R_i - \frac{N_{\alpha}\left(N_{\alpha}-1\right)}{2}\right)$$

  where N_{α} is the number of relevant images for the query, and R_i is the rank at which the i-th image is retrieved.
- This measure is 0 for perfect performance, and approaches 1 as performance worses.
- The average normalized rank ANR for the full dataset is given by:

$$ANR = \frac{1}{N}\sum_{\alpha=1}^{N} Rank\left(H_{\alpha}\right)$$

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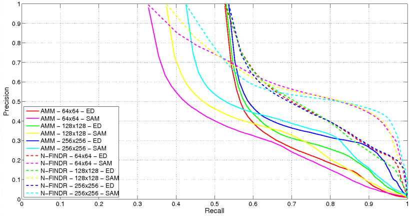
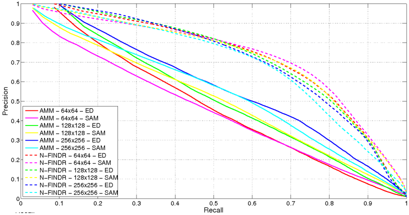
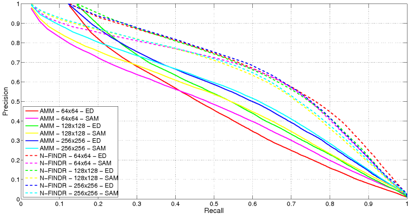
Precision-recall curves







ANR results

Spatial size	Distance	EIA	ANR 5-dataset	ANR 10-dataset	ANR 20-dataset
64×64	Euclidean	EIHA	0.0383	0.0442	0.0356
64×64	Euclidean	N-FINDER	0.0051	0.0120	0.0109
64×64	SAM	EIHA	0.0512	0.0559	0.0558
64×64	SAM	N-FINDER	0.0035	0.0145	0.0318
128×128	Euclidean	EIHA	0.0216	0.0306	0.0228
128×128	Euclidean	N-FINDER	0.0056	0.0108	0.0118
128×128	SAM	EIHA	0.0371	0.0440	0.0458
128×128	SAM	N-FINDER	0.0026	0.0153	0.0340
256×256	Euclidean	EIHA	0.0116	0.0186	0.0189
256×256	Euclidean	N-FINDER	0.0035	0.0119	0.0119
256×256	SAM	EIHA	0.0220	0.0368	0.0412
256×256	SAM	N-FINDER	0.0019	0.0180	0.0316

Summary

- The proposed spectral-spatial CBIR system is robust to the choice of EIA and between-endmembers distance function.
- We find that the N-FINDER has obtained better results in the sense that its precision-recall curves is systematically above the ones corresponding to the EIHA.

Future work

- Develop a retrieval feedback process:
  - Hard due to users limitations to evaluate hyperspectral data by visual inspection.
- Try new methodologies for CBIR systems validation without a-priori knowledge.
  - Presented in ESA-EUSC-JCR 2011 conference in Ispra (Italy).

Thanks for your attention

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