



Trabajos sobre imágenes hiperespectrales

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- Inducción de endmembers
- Segmentación robusta
- Acceso basado en contenidos a BD de imágenes hiperespectrales
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introducción

- Problema: segmentación no supervisada a través de “spectral unmixing”
- Aproximación: redes neuronales morfológicas que se convierten en redes neuronales basadas en “lattices”
 - Memorias asociativas de Ritter y Sussner



Introducción

- Problema: segmentación robusta a condiciones de iluminación
- Aproximación basada en la transformación a coordenadas esféricas
- Conseguir un equivalente a una componente cromática hiperespectral



Introducción

- Problema: caracterización de las imágenes hiperespectrales para acceso basado en contenidos (CBIR)
- Aproximación: caracterización de las imágenes por sus endmembers
 - Definición de una semi-métrica
 - Ampliación introduciendo información espacial



Introducción

- Problema: como validar los algoritmos si no tenemos la verdad del terreno
- Aproximación: generar una verdad del terreno sintetizada por otros medios.



Introducción

- Protagonistas:
 - Miguel A. Veganzones, PhD student,
 - Ramón Moreno, PhD student
- Colaboraciones
 - Gerhard Ritter, Univ. Florida
 - Peter Sussner, Univ. Campinas, Brasil
 - Mihai Datcu, DLR, Germany



Inducción de endmembers

- Planteamiento del problema
- Algunas soluciones e intentos
 - Metodos basados en independencia “lattice”
 - Usando las memorias como “detectores”
 - Extrayendo de las memorias los elementos



Spectral unmixing

- Modelo de mezcla espectral dado un conjunto de endmembers

$$\mathbf{x} = \sum_{i=1}^M a_i \mathbf{s}_i + \mathbf{w} = \mathbf{S}\mathbf{a} + \mathbf{w},$$

$$\sum_{i=1}^M a_i = 1$$

$$a_i \geq 0, i = 1, \dots, M.$$



Spectral unmixing

- Minimos cuadrados (LSE) no respeta las restricciones del modelo

$$\hat{\mathbf{a}} = (\mathbf{S}^T \mathbf{S})^{-1} \mathbf{S}^T \mathbf{x}.$$

- Minimos cuadrados no negativos (NNLSE) con suerte se cumplen las dos restricciones

minimizing $\|E\mathbf{a} - \mathbf{x}\|_2$

subject to $\mathbf{a} \geq \mathbf{0}$



Spectral unmixing

- El problema central es obtener un conjunto de endmembers
 - Librería obtenida a priori
 - Induciendolos a partir de los datos de la imagen
 - Metodos geométricos
 - Metodos de machine learning
 - Metodos basados en “lattice computing”



Memorias asociativas

- Morfological Associative Memories == Lattice Associative Memories

$$(X, Y) = \{(\mathbf{x}^\xi, \mathbf{y}^\xi); \xi = 1, \dots, k\}$$

$$W_{XY} = \bigwedge_{\xi=1}^k [\mathbf{y}^\xi \times (-\mathbf{x}^\xi)']$$

Memoria erosiva

$$M_{XY} = \bigvee_{\xi=1}^k [\mathbf{y}^\xi \times (-\mathbf{x}^\xi)']$$

Memoria dilatativa

Perfect recall

$$W_{XX} \square X = X = M_{XX} \square X$$



- Producto matricial “morfológico” o “lattice”

$$C = A \boxtimes B = [c_{ij}] \Leftrightarrow c_{ij} = \bigvee_{k=1..n} \{a_{ik} + b_{kj}\},$$

$$C = A \boxtriangle B = [c_{ij}] \Leftrightarrow c_{ij} = \bigwedge_{k=1..n} \{a_{ik} + b_{kj}\}.$$



- Dos aproximaciones iniciales
 - Extraer conjuntos de vectores independientes “lattice” de las filas y columnas de las memorias autoasociativas (Ritter)
 - Aplicar las memorias autoasociativas como detectores (nuestra)
 - Ambos son “un paso sobre la muestra”
- Manuel Graña, Ivan Villaverde, José Orlando Maldonado, Carmen Henandez, Two Lattice Computing approaches for the unsupervised segmentation of Hyperspectral Images, *Neurocomputing*, 72(2009):2111–2120



- Ritter: Conseguimos candidatos endmember a partir de las cols/filas de las MAM o LAM

Algorithm 1. Obtaining the subset of SLI vectors from a set X

- (1) Construct the W_{XX} and M_{XX} memories, consider the column vectors of the memories as the initial candidate sets of vectors $V = W$ and $N = M$. Work independently on them.
- (2) Iteratively remove one vector of the set of candidate vectors $V (N)$, for each reduced set of vectors $V' (N')$
 - (a) construct the memory $W_{V'V'} (W_{N'N'})$
 - (b) if $W_{XX} = W_{V'V'} (W_{XX} = W_{N'N'})$ then the vector removed is lattice dependent and can be definitively removed, so that $V (N)$ becomes $V' (N')$.



- Problema: demasiados endmembers
- Solución heurística: seleccionarlos en función de medidas de separación,
 - i.e. la varianza en cada dimensión



Algorithm 2. ETSA based on [24,28]

- (1) Given a set of vectors $X = \{\mathbf{x}^1, \dots, \mathbf{x}^k\} \subset \mathbb{R}^n$ compute the min and max auto-associative memories W_{XX} M_{XX} from the data. Their column vector sets W and M will be the candidate endmembers.
- (2) Register W and M relative to the data set adding the maximum and minimum values of the data dimensions (bands in the hyperspectral image). Obtain \overline{W} and \overline{M} as follows:
 - (a) Compute $u_i = \bigvee_{\xi=1}^n x_i^\xi$ and $v_i = \bigwedge_{\xi=1}^n x_i^\xi$.
 - (b) Compute $\overline{\mathbf{m}}^i = \mathbf{m}^i + v_i$ and $\overline{\mathbf{w}}^i = \mathbf{w}^i + u_i$
- (3) Remove lattice dependent vectors from the joint set $\overline{W} \cup \overline{M}$.
- (4) Compute the standard deviation along each dimension of the candidate endmember vectors, denoted by the vector $\vec{\sigma} = \{\sigma_1, \dots, \sigma_n\}$.
- (5) Assume the first vector in the set $\mathbf{v}_1 \in \overline{W} \cup \overline{M}$ as the first endmember, $E = \{\mathbf{v}_1\}$
- (6) Iterate for the remaining vectors $\mathbf{v} \in \overline{W} \cup \overline{M}$
 - (a) If $\|\mathbf{v} - \mathbf{e}\| < \gamma \vec{\sigma}$ for any $\mathbf{e} \in E$ then discard \mathbf{v} otherwise include \mathbf{v} in E



- La aproximación usando las LAM como filtros:
 - Construye las LAM usando los endmembers
 - Si el recall del pixel es perfecto → es dependiente, se descarta
 - Si independiente, testamos separación antes de añadirlo

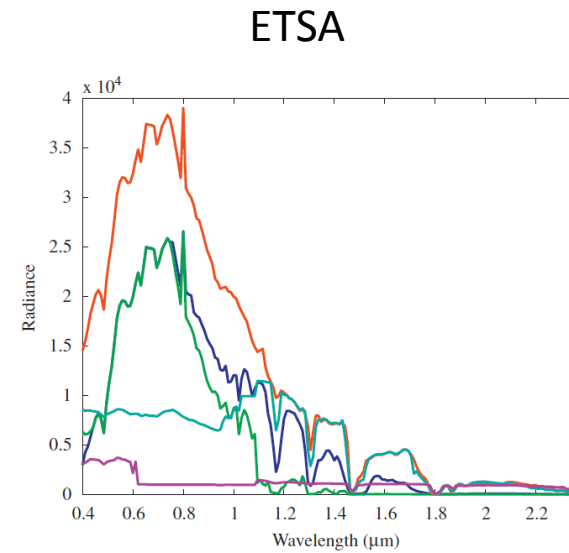
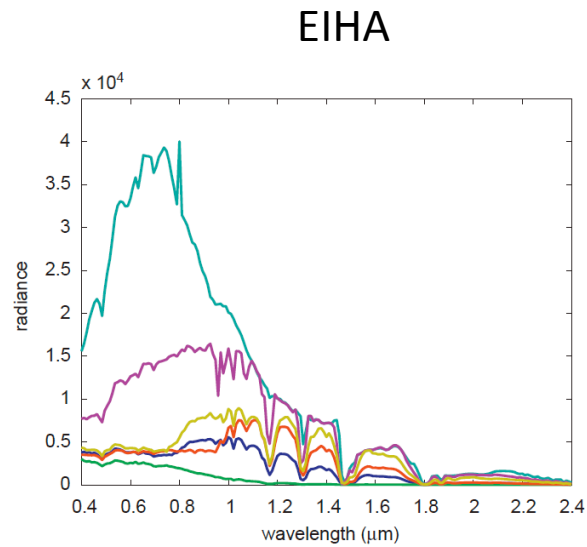


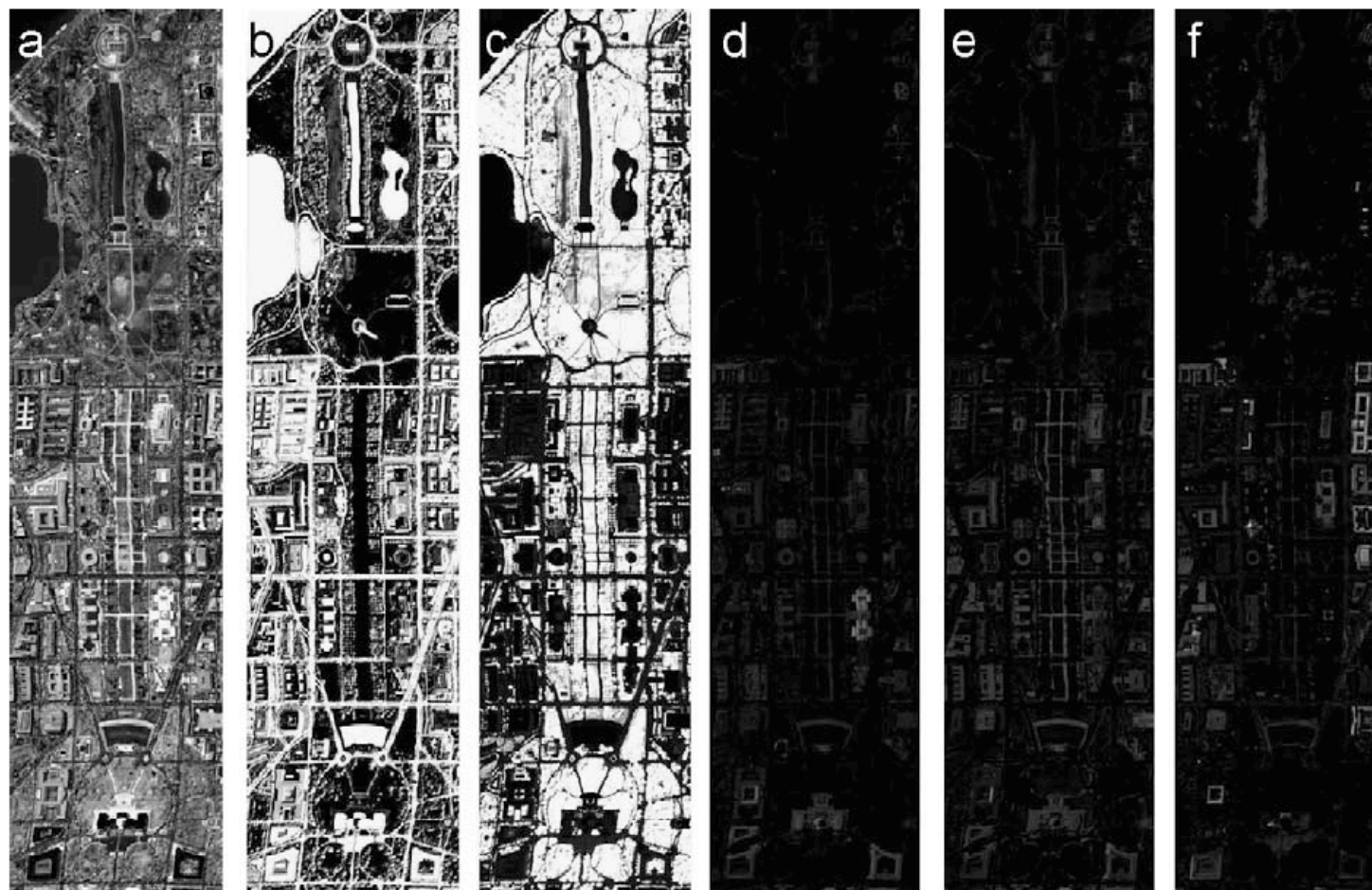
Algorithm 3. Endmember Induction Heuristic Algorithm (EIHA)

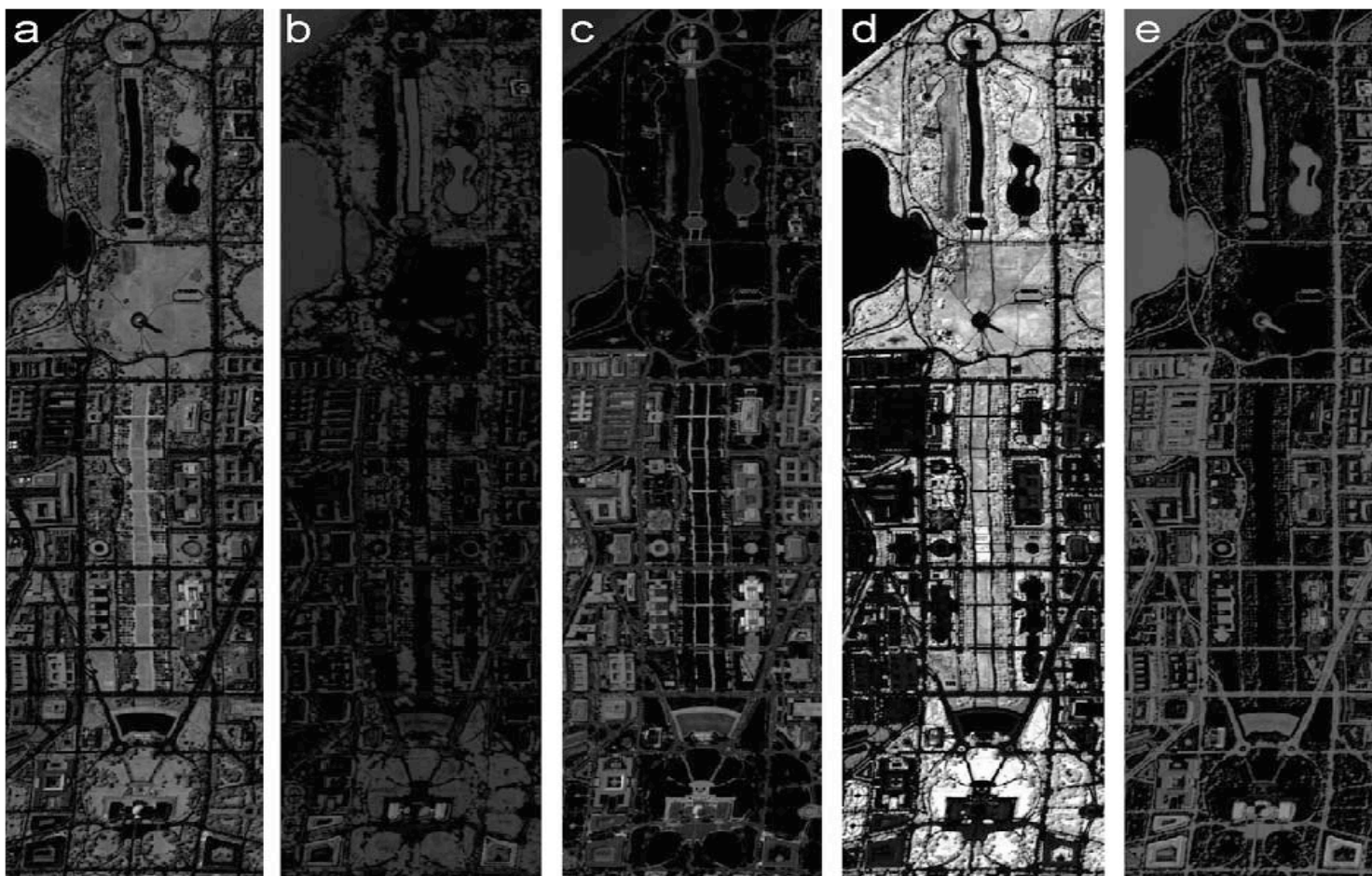
- (1) Shift the data sample to zero mean
 $\{\mathbf{f}^c(i) = \mathbf{f}(i) - \vec{\mu}; i = 1, \dots, n\}$.
- (2) Initialize the set of vertices $E = \{\mathbf{e}_1\}$ with a randomly picked sample. Initialize the set of lattice independent binary signatures
 $X = \{\mathbf{x}_1\} = \{(e_k^1 > 0; k = 1, \dots, d)\}$
- (3) Construct the AMMs based on the lattice independent binary signatures: M_{XX} and W_{XX} .
- (4) For each pixel $\mathbf{f}^c(i)$
 - (a) compute the noise corrections sign vectors $\mathbf{f}^+(i) = (\mathbf{f}^c(i) + \alpha \vec{\sigma} > \mathbf{0})$ and $\mathbf{f}^-(i) = (\mathbf{f}^c(i) - \alpha \vec{\sigma} > \mathbf{0})$
 - (b) compute $y^+ = M_{XX} \boxtimes \mathbf{f}^+(i)$
 - (c) compute $y^- = W_{XX} \boxtimes \mathbf{f}^-(i)$
 - (d) if $y^+ \notin X$ or $y^- \notin X$ then $\mathbf{f}^c(i)$ is a new vertex to be added to E , execute once 3 with the new E and resume the exploration of the data sample.
 - (e) if $y^+ \in X$ and $\mathbf{f}^c(i) > \mathbf{e}_{y^+}$ the pixel spectral signature is more extreme than the stored vertex, then substitute \mathbf{e}_{y^+} with $\mathbf{f}^c(i)$.
 - (f) if $y^- \in X$ and $\mathbf{f}^c(i) < \mathbf{e}_{y^-}$ the new data point is more extreme than the stored vertex, then substitute \mathbf{e}_{y^-} with $\mathbf{f}^c(i)$.
- (5) The final set of endmembers is the set of original data vectors $\mathbf{f}(i)$ corresponding to the sign vectors selected as members of E .



- Resultados sobre “washington dc”









- Mejorando la aproximación de Ritter:
 - selección mediante algoritmos genéticos multi-objetivo
 - Criterios (minimización):
 - Error residual del spectral unmixing

$$f_{\text{RMSE}}(E) = \text{RMSE}(E, X) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x}_i - E\alpha_i)^2,$$

- Complejidad de la solución

$$f_{|\cdot|}(E) = \frac{|E|}{|E_{\text{WM}}|},$$

- Endmember induction by Lattice Associative Memories and Multi-Objective Genetic Algorithms Manuel Graña , Miguel A. Veganzones



- Versión “acelerada”
- Criterios
 - Correlación entre endmembers

$$f_{\text{CORR}}(E) = \max \{c_{ij}; e_i, e_j \in E\},$$

- complejidad

$$f_{|\cdot|^{-1}}(E) = \frac{|E_{\text{WM}}|}{|E|}.$$



Algorithm 1 Pseudo-code specification of the WM algorithm.

1. L is the number of the spectral bands and N is the number of data samples.
2. Calculate $\mathbf{v} = [v_1, \dots, v_L]$ and $\mathbf{u} = [u_1, \dots, u_L]$,

$$v_k = \min_{\xi} x_k^{\xi}; u_k = \max_{\xi} x_k^{\xi}$$

for all $k = 1, \dots, L$ and $\xi = 1, \dots, N$,

3. Compute the LAAMs

$$\mathbf{W}_{XX} = \bigwedge_{\xi=1}^N [\mathbf{x}^{\xi} \times (-\mathbf{x}^{\xi})']; \mathbf{M}_{XX} = \bigvee_{\xi=1}^N [\mathbf{x}^{\xi} \times (-\mathbf{x}^{\xi})']$$

where \times is any of the \boxtimes or \boxminus operators.

4. Build $W = \{\mathbf{w}^1, \dots, \mathbf{w}^L\}$ and $M = \{\mathbf{m}^1, \dots, \mathbf{m}^L\}$ such that

$$\mathbf{w}^k = u_k + \mathbf{W}^k; \mathbf{m}^k = v_k + \mathbf{M}^k; k = 1, \dots, L.$$

5. Return the set $V = W \cup M \cup \{\mathbf{v}, \mathbf{u}\}$.
-

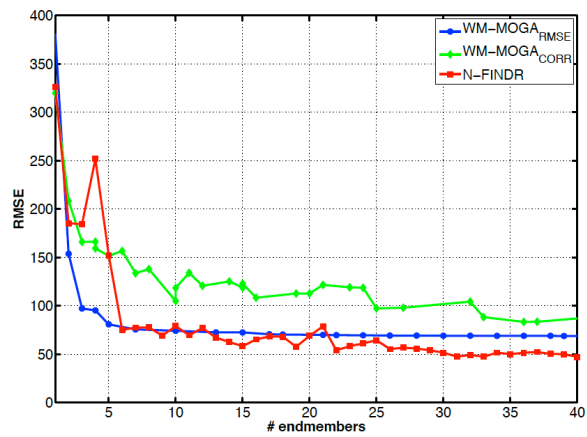


Algorithm 2 Pseudo-code for the WM-MOGA process

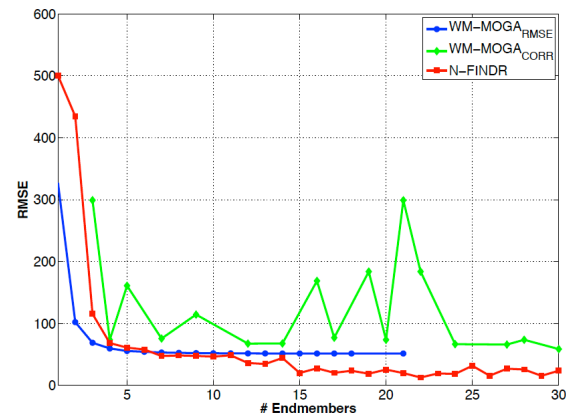
1. Apply $WM(X)$ to obtain $E_{WM} = \{e^1, \dots, e^p\}$
 2. Apply MOGA (E_{WM}) to obtain the Pareto set of solutions $\mathbf{P} = \{E^i, i = 1, \dots, q\}$
 3. Apply the Occam razor selecting $E^*(\epsilon) = \arg \min_{\mathbf{P}} \left\{ \left| \frac{f_{RMSE}(E^{i+1})}{f_{RMSE}(E^i)} - \frac{f_{RMSE}(E^i)}{f_{RMSE}(E^{i-1})} \right| < \epsilon \right\}$
 4. Return $E^*(\epsilon)$
-

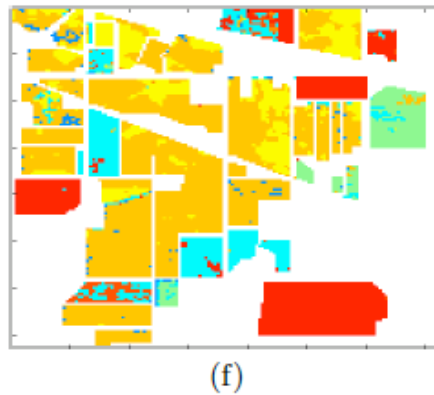
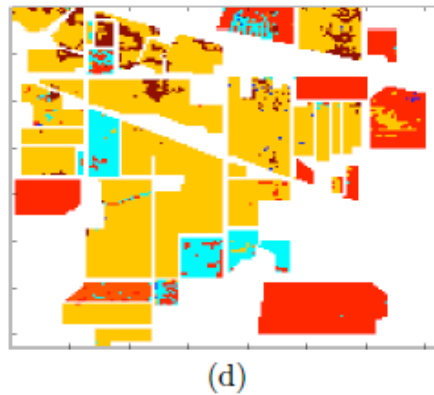
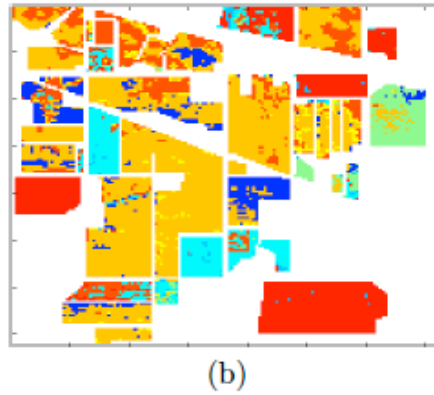
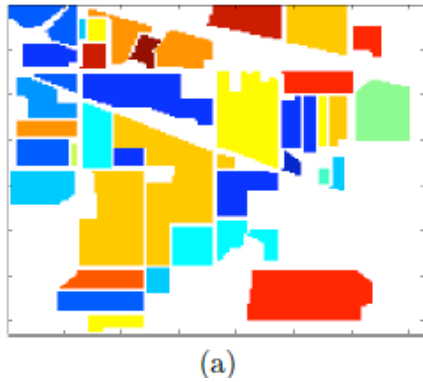


Pareto set Indian Pines

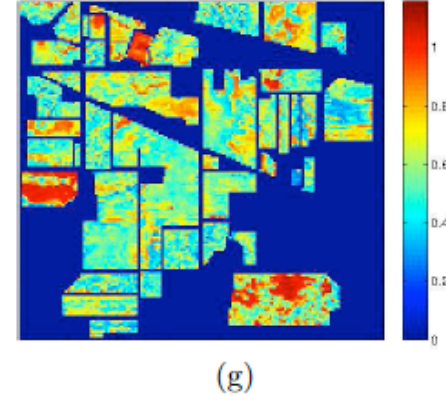
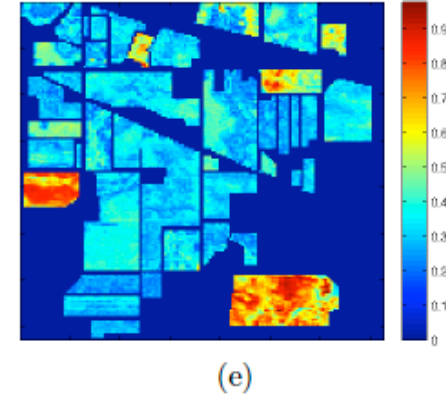
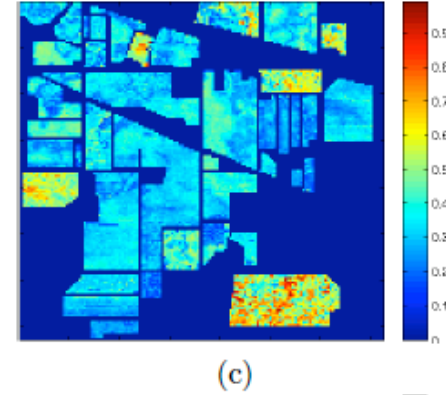


Pareto set Salinas





Thematic map

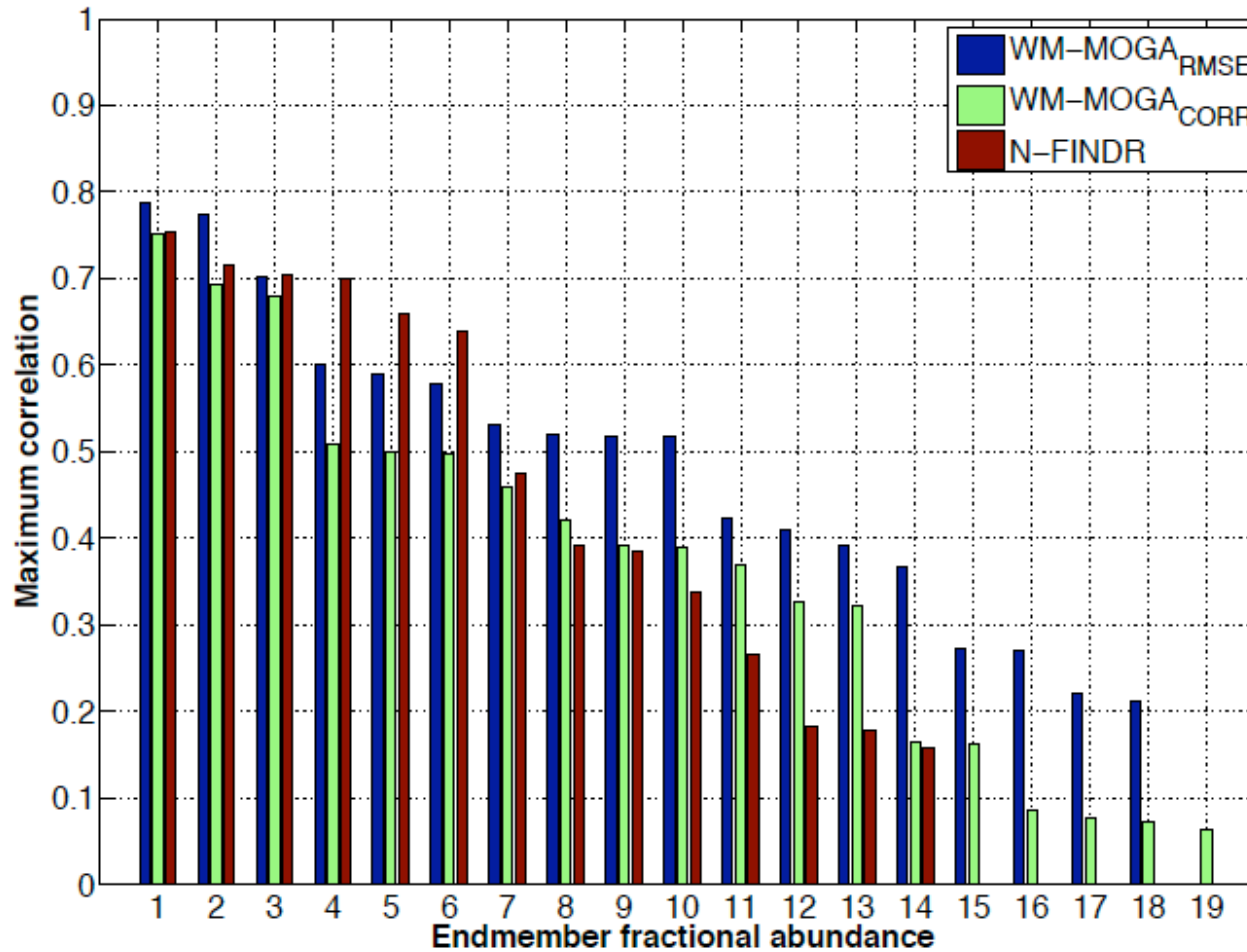


Max abundance per pixel

WM-MOGA

WM-MOGA-CORR

N-FINDR

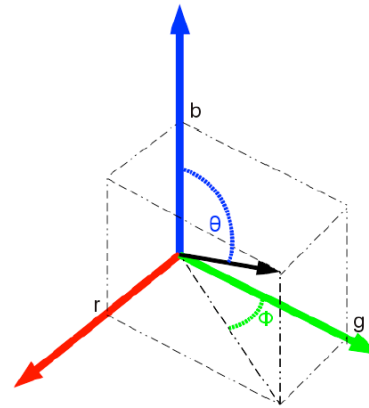


Indian pines: maximum correlation with the ground truth per endmember



Segmentación robusta

- Observación: en coordenadas esféricas
 - La magnitud es el componente de luminancia
 - Los ángulos son componentes cromáticos

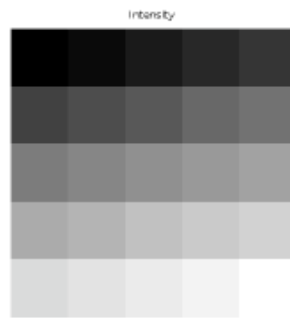


» Hybrid Gradient for n-Dimensional Images through Hyperspherical Coordinates Ramón Moreno , Manuel Graña, HAIS 2012



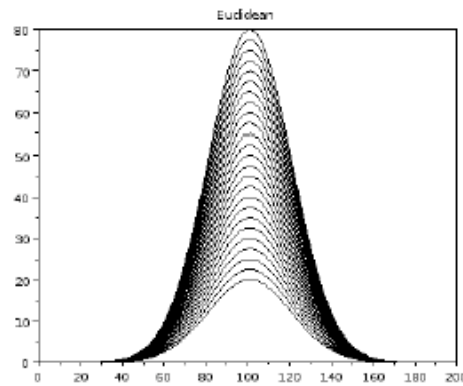
- De coordenadas euclídeas a esféricas

$$\begin{aligned}l &= \sqrt{v_1^2 + v_2^2 + v_3^2 + \dots + v_n^2} \\ \phi_1 &= \arctan \frac{v_1}{\sqrt{v_2^2 + v_3^2 + \dots + v_n^2}} \\ \phi_2 &= \arctan \frac{v_2}{\sqrt{v_3^2 + v_4^2 + \dots + v_n^2}} \\ &\vdots \\ \phi_{n-2} &= \arctan \frac{v_{n-2}}{\sqrt{v_{n-1}^2 + v_n^2}} \\ \phi_{n-1} &= 2 \cdot \arctan \frac{\sqrt{v_{n-1}^2 + v_n^2} - v_{n-1}}{v_n}\end{aligned}$$



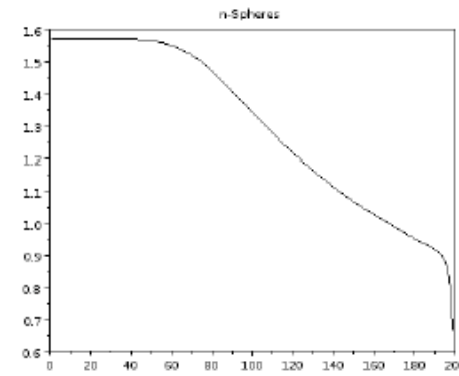
(a)

Luminancia



(b)

Perfil espectral euclideo



(c)

Perfil espectral comun en
Coordenadas esféricas



- Operador gradiente

$$\nabla I(i, j) = \begin{bmatrix} G_i(i, j) \\ G_j(i, j) \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial i} I(i, j) \\ \frac{\partial}{\partial j} I(i, j) \end{bmatrix} :$$

$$G(i, j) = |G_i(i, j)| + |G_j(i, j)|.$$

$$\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$



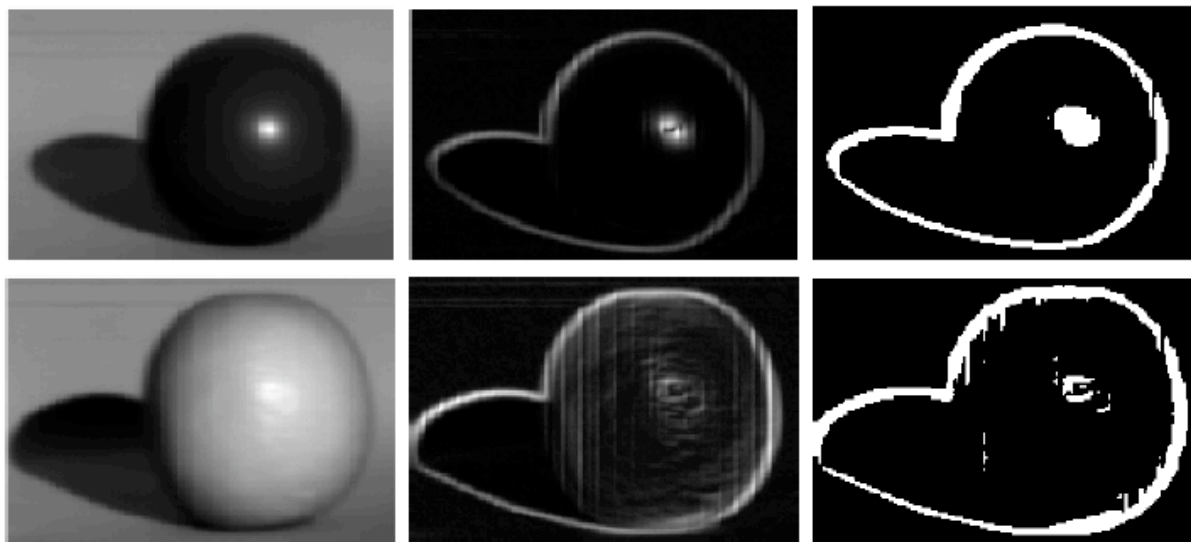
- Gradiente cromático hiperespectral

Distancia cromática $dc(p, q) = \sqrt{\sum_{i=1}^{n-1} \|\bar{\phi}_{p,i} - \bar{\phi}_{q,i}\|^2}$

Gradientes por
filas y columnas $CG_R(\mathbf{C}(i, j)) = \sum_{r=-1}^1 dc(\mathbf{C}(i-r, j+1), \mathbf{C}(i-r, j-1)),$

$$CG_C(\mathbf{C}(i, j)) = \sum_{c=-1}^1 dc(\mathbf{C}(i+1, j-c), \mathbf{C}(i-1, j-c)),$$

Gradiente cromático $CG(x) = CG_R(x) + CG_C(x)$



. Classical Prewitt gradient (on each band) of two hyperspectral images

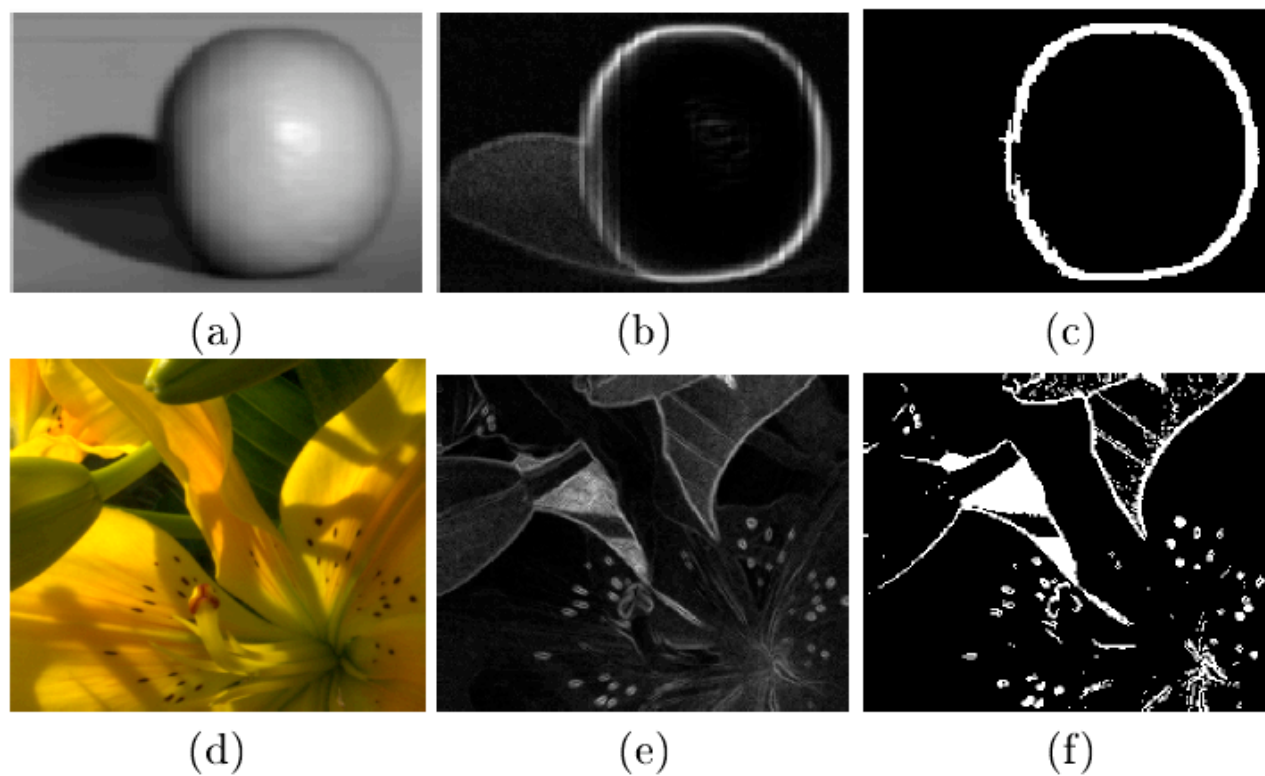


Fig. 5. Chromatic gradient

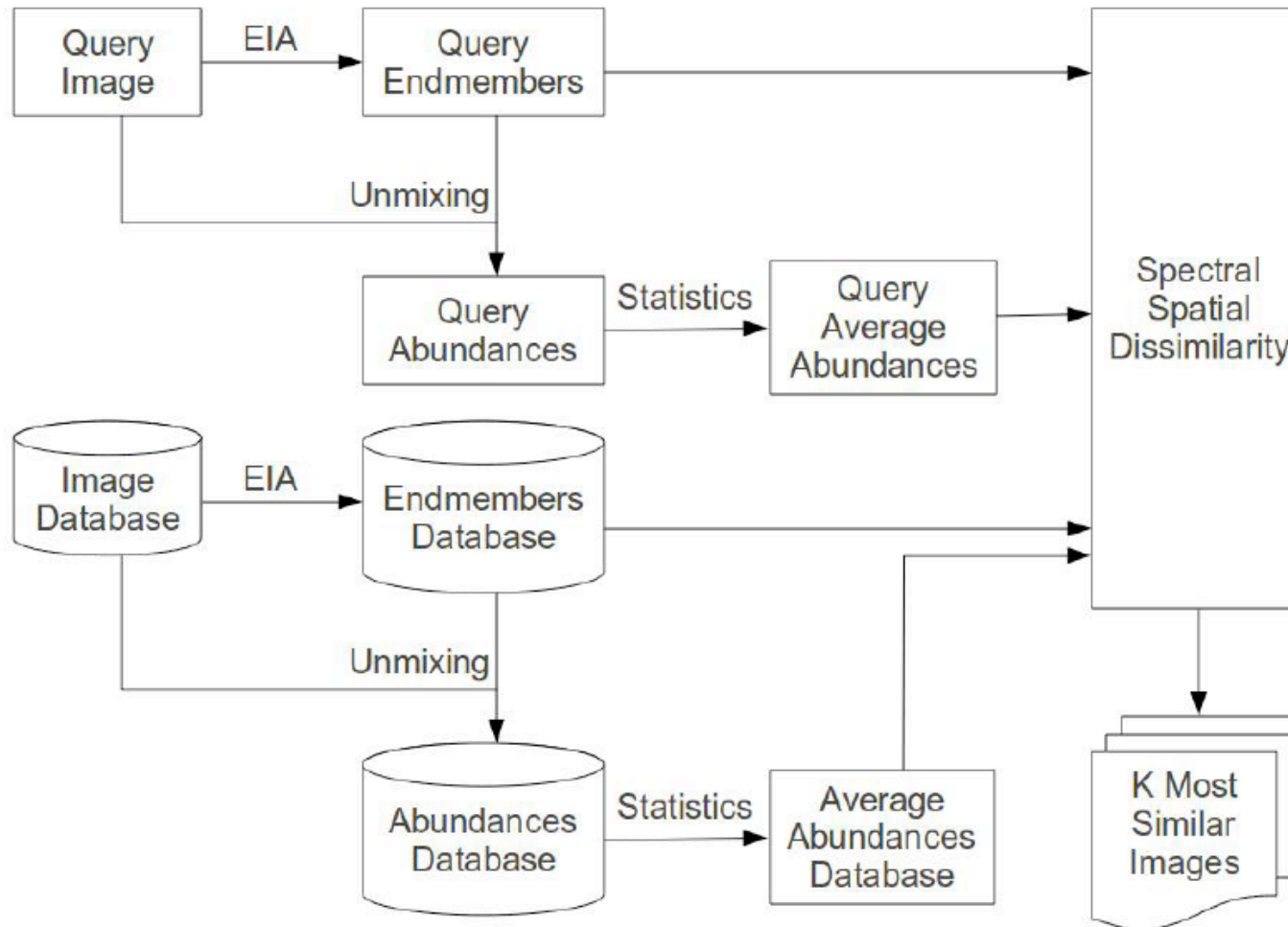


Acceso a BD basada en contenidos

- La caracterización de las imágenes se hace en términos de los endmembers
 - Espectral: solo los endmembers
 - Espacial/espectral: usando información de las abundancias
- Definición de una medida de similitud apropiada
- Validación sobre imágenes sintéticas
 - A Spectral/Spatial CBIR system for hyperspectral images Miguel Angel Veganzones, Manuel Graña, J-STARS en revisión



CBIR





Disimilitud espectral/espacial

hyperspectral image H_α (E_α, Φ_α)

$$E_\alpha = \{e_1^\alpha, e_2^\alpha, \dots, e_{m_\alpha}^\alpha\} \quad \text{Endmembers inducidos}$$

Distancias entre pares de endmembers de dos imagenes

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

$$\Phi_\alpha = \{\phi_1^\alpha, \phi_2^\alpha, \dots, \phi_{m_\alpha}^\alpha\} \quad \text{Mapas de abundancias}$$

$$\bar{\Phi}_\alpha = \{\bar{\phi}_1^\alpha, \bar{\phi}_2^\alpha, \dots, \bar{\phi}_{m_\alpha}^\alpha\} \quad \text{Abundancia promedio para cada endmember}$$



Disimilitud espectral/espacial

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

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

Algorithm 1 Significance credits assignment algorithm.

- 1) Set $\mathcal{L} = \{\}$.
 - 2) Denote $\mathcal{M} = \{(i, j) : i = 1, \dots, m_\alpha; j = 1, \dots, m_\beta\}$.
 - 3) Choose the minimum d_{ij} for $(i, j) \in \mathcal{M} - \mathcal{L}$. Label the corresponding (i, j) as (i', j') .
 - 4) $r_{i'j'} = \min \{\bar{\phi}_{i'}^\alpha, \bar{\phi}_{j'}^\beta\}$.
 - 5) If $\bar{\phi}_{i'}^\alpha < \bar{\phi}_{j'}^\beta$, set $r_{ij} = 0$, for all $j \neq j'$; otherwise, set $r_{ij'} = 0$, for all $i \neq i'$.
 - 6) If $\bar{\phi}_{i'}^\alpha < \bar{\phi}_{j'}^\beta$, set $\bar{\phi}_{i'}^\alpha = 0$ and $\bar{\phi}_{j'}^\beta = \bar{\phi}_{j'}^\beta - \bar{\phi}_{i'}^\alpha$; otherwise, set $\bar{\phi}_{j'}^\beta = 0$ and $\bar{\phi}_{i'}^\alpha = \bar{\phi}_{i'}^\alpha - \bar{\phi}_{j'}^\beta$.
 - 7) $\mathcal{L} = \mathcal{L} + \{(i', j')\}$.
 - 8) If $\sum_{i=1}^{m_\alpha} \bar{\phi}_i^\alpha > 0$ and $\sum_{j=1}^{m_\beta} \bar{\phi}_j^\beta > 0$, go to step 3; otherwise, stop.
-



- Medidas de rendimiento para validacion

$$p = \frac{|T \cap R|}{|T|} \quad \text{precision} \quad P_k = \frac{1}{N} \sum_{\alpha=1}^N P_k(H_\alpha)$$

$$r = \frac{|T \cap R|}{|R|} \quad \text{recall} \quad R_k = \frac{1}{N} \sum_{\alpha=1}^N R_k(H_\alpha).$$

$$\text{Rango/orden} \quad \text{Rank}(H_\alpha) = \frac{1}{NN_\alpha} \left(\sum_{i=1}^{N_\alpha} \Omega_\alpha^i - \frac{N_\alpha(N_\alpha - 1)}{2} \right),$$

$$\text{Rango promedio} \quad ANR = \frac{1}{N} \sum_{\alpha=1}^N \text{Rank}(H_\alpha).$$



- Validacion con imágenes sinteticas:
 - Generamos una colección extensa con varios tamaños, numeros de endmembers y ruido
 - Calculamos los rendimientos en un esquema “leave-one-out”

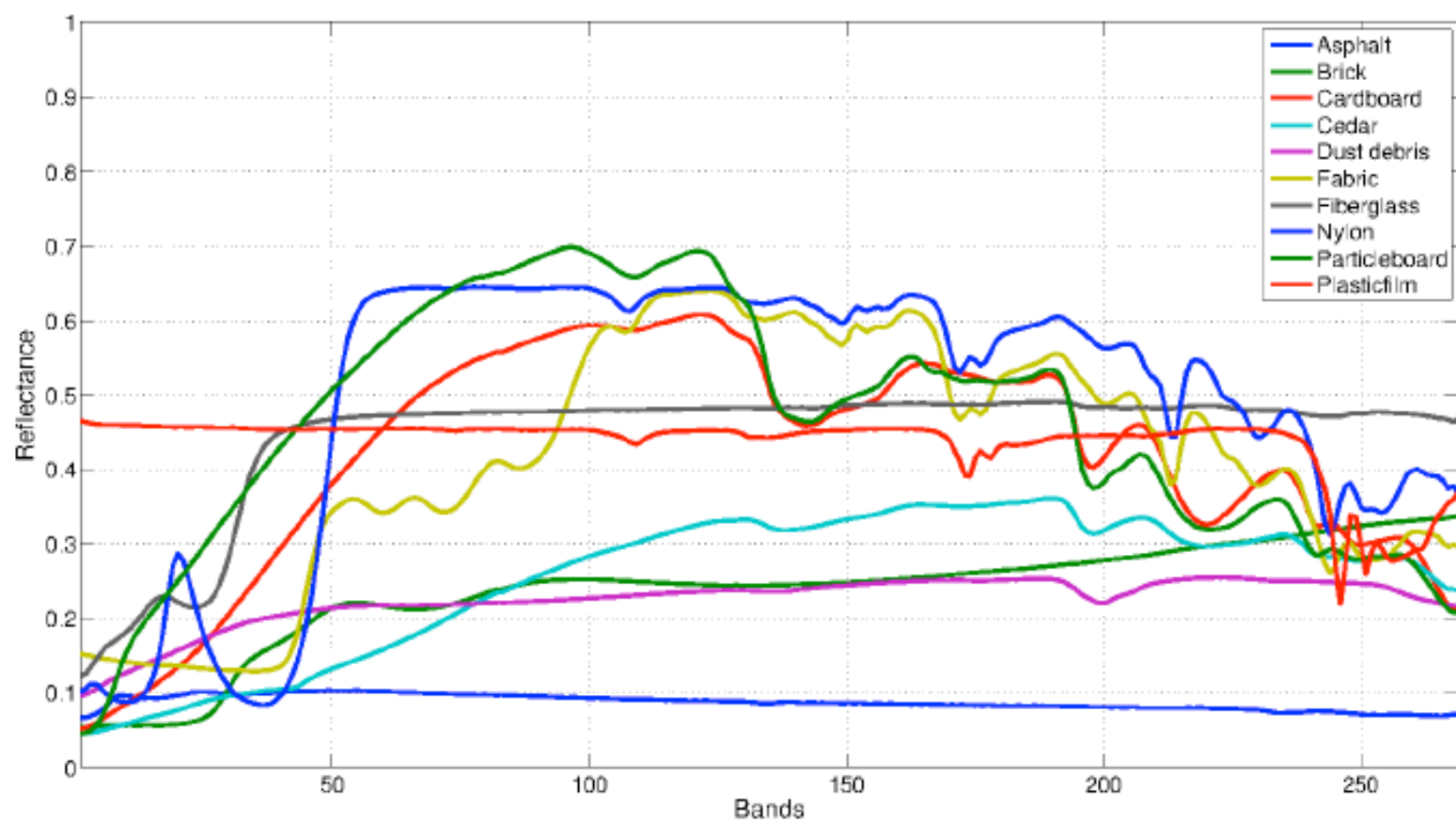


Figure 2. Pool of endmembers selected from the USGS spectral library.

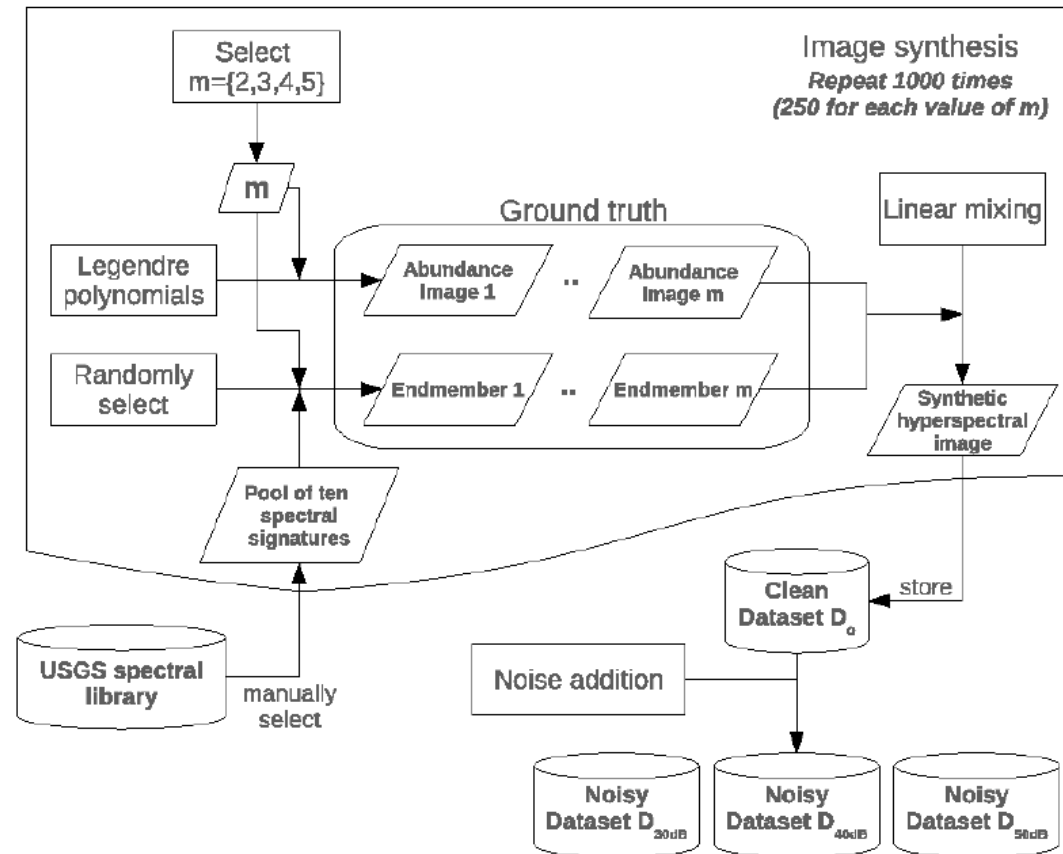
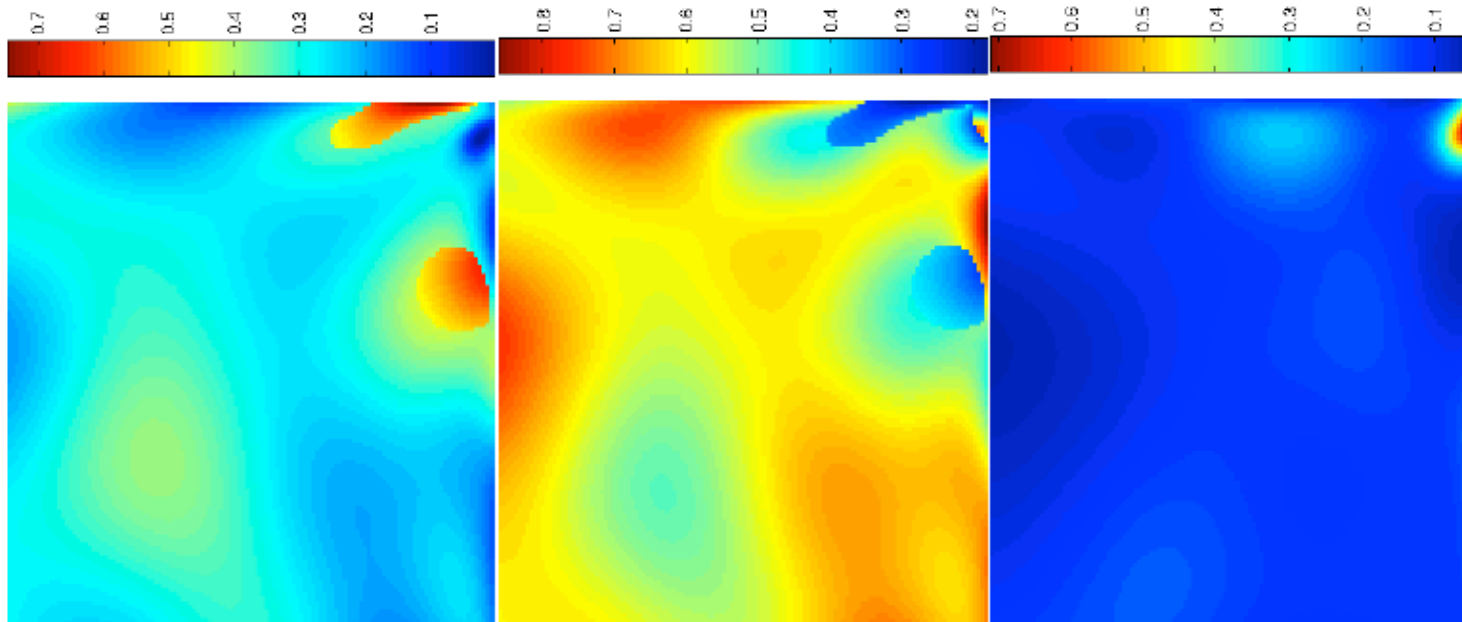
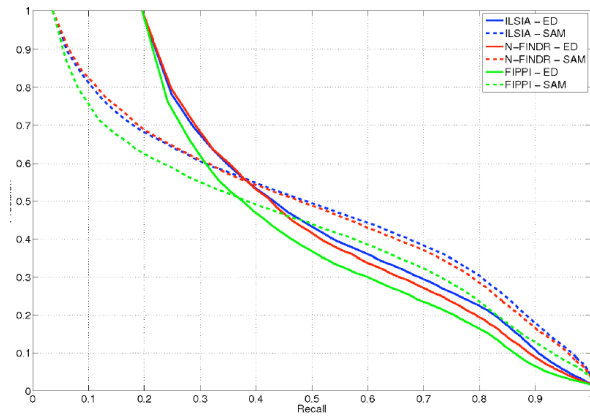


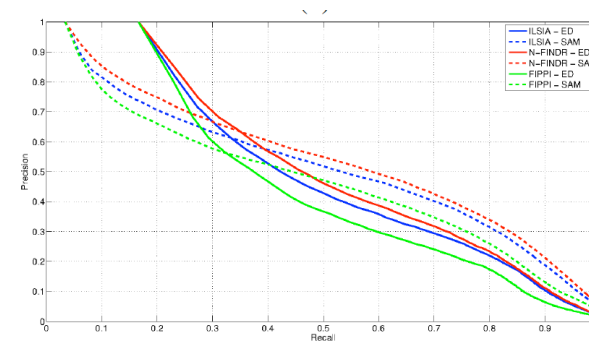
Figure 4. Flow diagram of the hyperspectral datasets synthesis process.



3 imágenes de abundancia sintéticas generadas como productos de polinomios de Legendre



(a)



(b)

Precision y recall para imágenes sin ruido de tamaños (a) 64x64 y (b) 128x128



Averaged Normalized Rank (ANR)						
Dataset	ILSIA		N-FINDR		FIPPI	
	ED	SAM	ED	SAM	ED	SAM
$D_o^{(64)}$	0.043	0.053	0.050	0.058	0.064	0.074
$D_{30dB}^{(64)}$	0.045	0.101	0.043	0.097	0.043	0.099
$D_{40dB}^{(64)}$	0.042	0.057	0.036	0.048	0.037	0.052
$D_{50dB}^{(64)}$	0.042	0.053	0.038	0.045	0.041	0.051

(a)

Averaged Normalized Rank (ANR)						
Dataset	ILSIA		N-FINDR		FIPPI	
	ED	SAM	ED	SAM	ED	SAM
$D_o^{(128)}$	0.047	0.057	0.044	0.050	0.068	0.077
$D_{30dB}^{(128)}$	0.044	0.086	0.044	0.088	0.038	0.082
$D_{40dB}^{(128)}$	0.044	0.056	0.035	0.043	0.039	0.049
$D_{50dB}^{(128)}$	0.043	0.052	0.033	0.038	0.040	0.047

(b)

Table II
ANR RESULTS FOR SYNTHETIC DATASETS: (A) $D^{(64)}$ (B) $D^{(128)}$.

Resultados sumarios para los conjuntos de datos, los algoritmos de inducción y las distancias elementales



- Experimento sobre una imagen real, partida en trozos



(a)

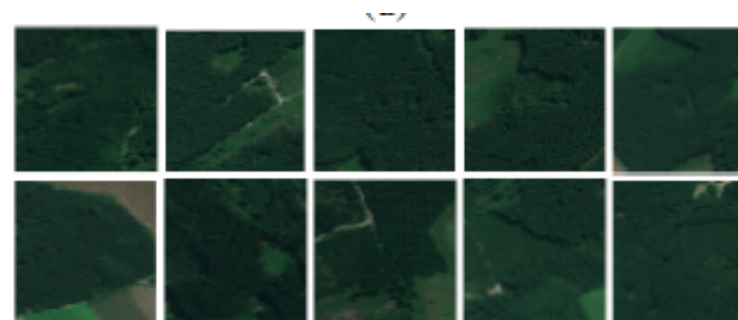
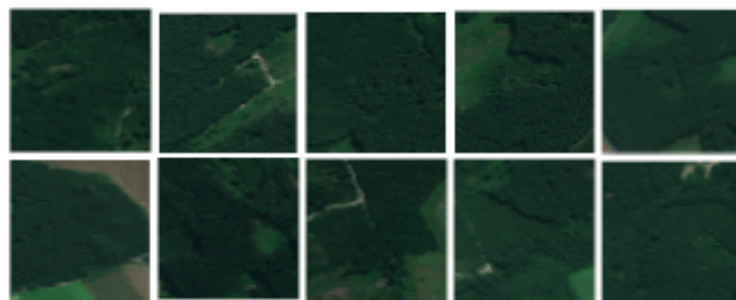
query



Euclidea



SAM



ILSIA (lattice computing)

N-FINDR



Recursos publicados

- Escenas hyperspectrales generales
 - http://www.ehu.es/ccwintco/index.php/Hyperspectral_Remote_Sensing_Scenes
- Código de síntesis de imágenes hiperespectrales
 - http://www.ehu.es/ccwintco/index.php/Hyperspectral_Imagery_Synthesis_tools_for_MATLAB
- Código de inducción de endmembers, incluyendo memorias autoasociativas LAM
 - http://www.ehu.es/ccwintco/index.php/Endmember_Induction_Algorithms_%28EIAs%29_for_MATLAB_and_SCILAB
- Una colección de imágenes “in-house”
 - http://www.ehu.es/ccwintco/index.php/Hyperspectral_Camera_SOC710_Datasets
- Código de segmentación cromática (RGB por ahora)
 - http://www.ehu.es/ccwintco/index.php/Hybrid_Image_Segmentation