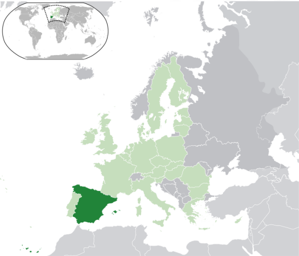
# A sourvey of (my) image segmentation

Ramón Moreno

Computational Intelligence Group
University of the Basque Country, Spain

November 29, 2011

# Where I come from



# Where I come from

# Where I come from

# Where I come from

eman ta zabal zazu

UPV EHU

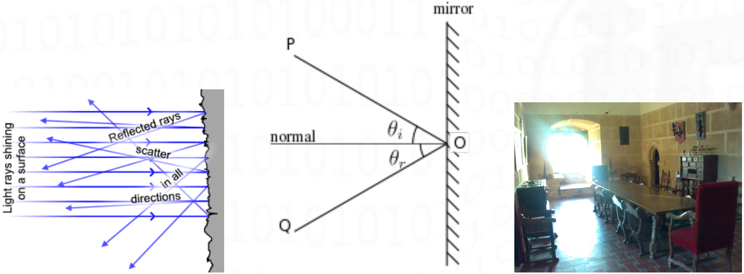

About me

1. DRM
2. On the RGB
    1. ISC
    2. Chromatic Gradient
    3. Hybrid Gradient
    4. Watershed Segmentation
3. On n-Dimensional Spaces
    1. A door for Basic Colorimetry
    2. Chromatic Gradient (ICPRAM)
    3. Hybrid Gradient (HAIS)
    4. A Case of Supervised Segmentation
    5. A Case of Unsupervised Segmentation

# Dichromatic Reflection Model

- The dichromatic reflection model was proposed by Shafer [?]
- The dichromatic reflection model describes the surface reflection of light in dielectric materials as the sum of two components, the **diffuse** and **specular** terms.
- The **diffuse reflection** component exhibits the color of the material. Different light wavelengths are more or less absorbed as light is scattered by the material.
- The **specular reflection** component is essentially determined by the color of incident light.

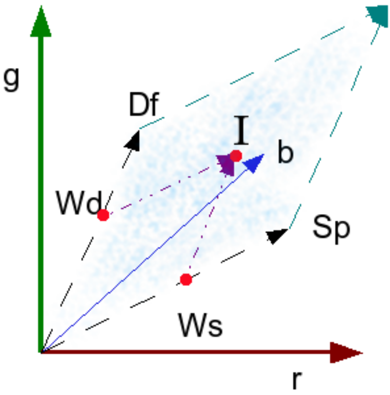
# Diffuse and Specular reflections




(a) (b) (c)

Figure: Diffuse reflection(a), specular reflection(b), natural image(c)

# Dichromatic Reflection Model




Chromaticity Space for DRM

| | |
|---|---|
| Normalized | RGB ( $r + g + b = 1$) |
| Df | Diffuse component |
| Sp | Specular component |
| Wd | Weighting factor of Df |
| Ws | Weighting factor of Sp |
| I | Sample Intensity value |

# Dichromatic Reflection Model

- Algebraically, the DRM is

$$I(x) = m_d(x)D + m_s(x)S$$

- When there are several colors in the imaged scene, the DRM becomes $I(x) = m_d(x)D(x) + m_s(x)S$. Notice that $D$ depends on the spatial coordinates $x$.
- In Spherical Coordinates

$$\mathbf{I}(\mathbf{x}) = (\theta_\mathbf{D}(\mathbf{x}), \phi_\mathbf{D}(\mathbf{x}), l_\mathbf{D}(\mathbf{x})) + (\theta_\mathbf{S}, \phi_\mathbf{S}, l_\mathbf{S}(\mathbf{x}))$$

# Experimental results

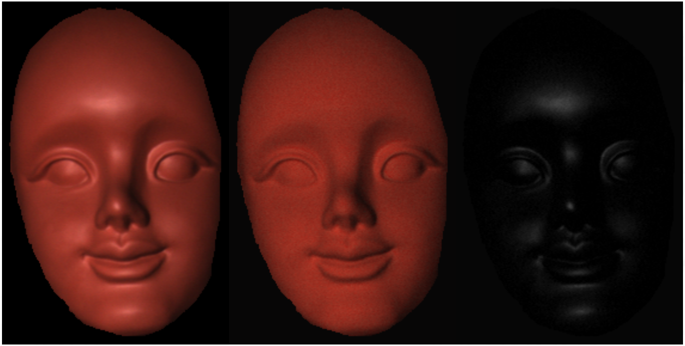
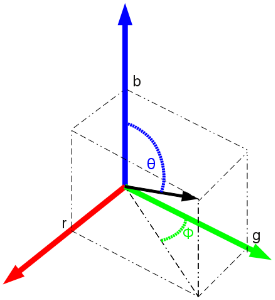


Figure: Natural image, diffuse image and specular image

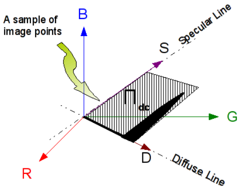
# (ISC)

Illumination Source Chromaticity Estimation
A key sptep before color image processing.
It provides robustness respect to the illumination changes
Image normalization

# (ISC) Spheric Coordinates

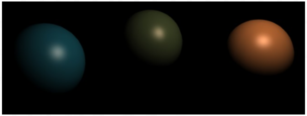



spheric coor.

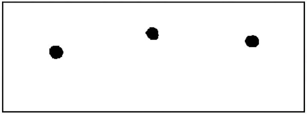



DRM on RGB

# (ISC) Spheric Coordinates

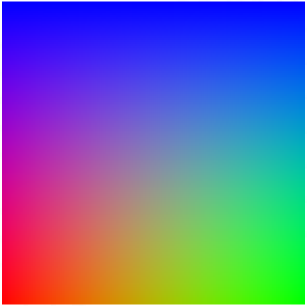


img.

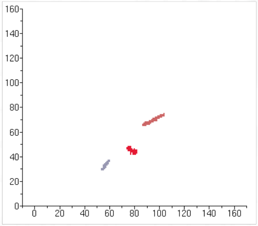


Specular ixels

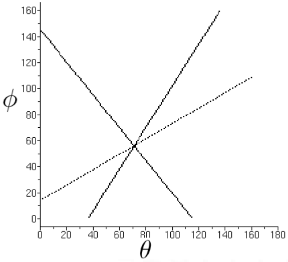
# (ISC) Chromatic Space



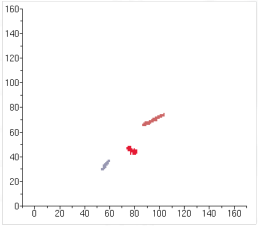
Zenith-Azimuth Space



# (ISC)




interpolated lines



# Chromatic Gradient

Chromatic Gradient

# Gradient

## Definition of the image gradient

- To set the stage for our chromatic gradient proposition, we must recall the definition of the image gradient

$$G[I(i,j)] = \begin{bmatrix} G_i \\ G_j \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial i} I(i,j) \\ \frac{\partial}{\partial j} I(i,j) \end{bmatrix}, \quad (1)$$

where $f(i,j)$ is the image function at pixel $(i,j)$. For edge detection, the usual convention is to examine the gradient magnitude:

$$G(I) = |G_i| + |G_j|. \quad (2)$$

# Gradient

## Problem: The intensity approach

- For color images, the basic approach to perform edge detection is to drop all color information, computing the intensity $Intensity = (Red + Green + Blue)/3$ (sometimes computed as $Intensity = .2989 * Red + .587 * Green + .114 * Blue$)
- To take into account color information, the easiest approach is to apply the gradient operators to each color band image and to combine the results afterwards:

$$G(I) = [G(I_r) + G(I_g) + G(I_b)]/3$$

# Gradient

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

(a)

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

(b)

Figure: Convolution kernels for the (a) Sobel and (b) Prewitt edge detection operators.

# Gradient

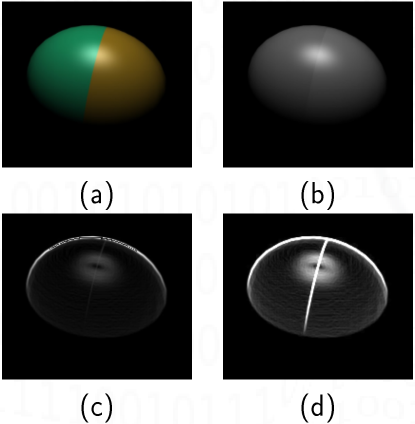



Figure: (a) Original synthetic RGB image, (b) Intensity image, (c) Gradient magnitude computed on the intensity image, (d) gradient magnitude combining the gradient magnitudes of each color band

# A chromatic coherent RGB pixels distance

## Notation

- First, we convert the RGB cartesian coordinates of each pixel to polar coordinates, withe the black color as the RGB space origin.
- We denote the cartesian coordinate image as $I = \left\{ (r, g, b)_p ; p \in \mathbb{N}^2 \right\}$
- And the spherical coordinate as $P = \left\{ (\phi, \theta, l)_p ; p \in \mathbb{N}^2 \right\}$, where $p$ denotes the pixel position.
  - In this second expression, we discard the $l$ because it does not contain chromatic information.

# A chromatic coherent RGB pixels distance

## Chromatic distance

- For a pair of image pixels $p$ and $q$, the color distance between them is defined as:

$$\angle(P_p, P_q) = \sqrt{(\theta_q - \theta_p)^2 + (\phi_q - \phi_p)^2}, \tag{3}$$

  that is, the color distance corresponds to the euclidean distance of the Azimuth and Zenith angles of the pixel's RGB color spherical representation.
- This distance is not influenced by the intensity and, thus, will be robust against specular surface reflections.

# Chromatic coherent gradient operators

## Chromatic Gradient

- We will formulate a pair of Prewitt-like gradient convolution operations on the basis of the above distante.
- Note that the $\angle(P_p, P_q)$ distance is always positive.
- Prewitt masks

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

# Chromatic coherent gradient operators

## Chromatic Gradient

- The row convolution is defined as

$$CG_R(P(i,j)) = \sum_{r=-1}^{1} \angle(P(i-r,j+1), P(i-r,j-1))$$

- And the column convolution is defined as

$$CG_C(P(i,j)) = \sum_{c=-1}^{1} \angle(P(i+1,j-c), P(i-1,j-c))$$

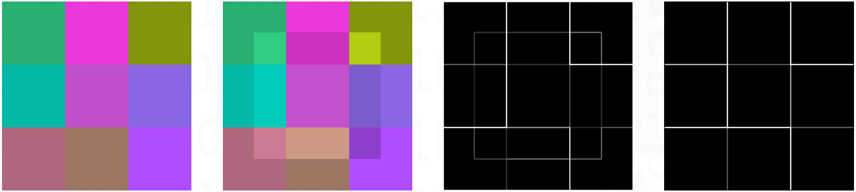
- The color gradient image is computed as:

$$CG(P) = CG_R(P) + CG_C(P) \quad (4)$$

# Experimental Results

- To demonstrate the efficiency of our proposed approach, we will show three experimental results.
- Two of the experiments are done on synthetic images whose ground truth is know.

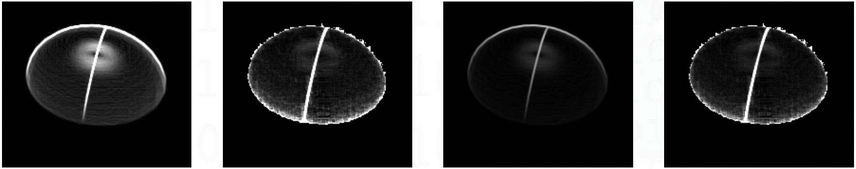
# Experimental Results I



(a) (b) (c) (d)

Figure: Results of the color edge detection on a synthetic image with nine uniform chromatic regions and a variation of intensity. (a) Original color distribution, (b) lower intensity central square, (c) Prewitt detection on RGB bands, (c) our approach in equation (4).

# Experimental Results



(a) (b) (c) (d)

Sobel Prewitt

Figure: Color edge on the synthetic image of fig. 4(a) with two color regions. (a) The Sobel operator over the RGB bands with specular component, (b) our approach in a Sobel-like structure, (c) the Prewitt linear operator, (d) our approach in a Prewitt like structure.

# Experimental Results

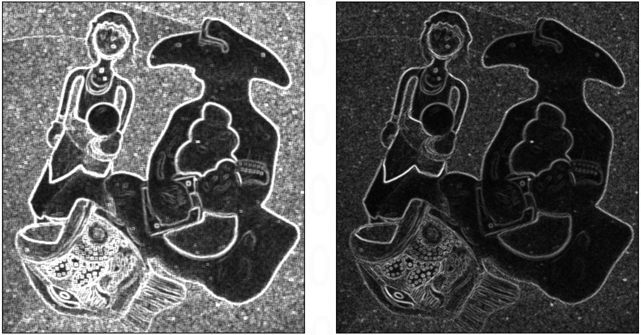
Figure: Natural image

# Experimental Results

(a) (b)

Figure: Results of the linear operators on the natural image (a) Sobel detector, (b) Prewitt detector

# Experimental Results



(a) (b)

Figure: Resuls of our approach on the natural image (a) taking 8 neighbors, (b) taking 4 neighbors

# Hybrid Distance for Image Segmentation

Hybrid Distance for Image Segmentation

# Hybrid Distance

- This transition is expressed with the graph showed in the Fig. 10.

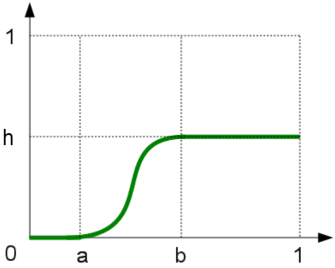



Figure: Chromatic activation function $\alpha$

# Hybrid Distance

- For values below $a$ it is inactive.
- For values between $a$ and $b$ it goes from its minimum energy to its maximum energy $h$ following a sinusoidal shape.
- Finally for values bigger that $b$ its energy is always $h$.
- The three parameters $a, b, h$ are in the range $[0, 1]$.
- The region under the green line is the chromatic importance
- The region over this line is the intensity importance.

# Hybrid Distance

The function $\alpha(I)$ depends of the image intensity $I$.Its mathematical expression is as follows:

$$\alpha(I) = \begin{cases} 0 & I \leq a \\ \frac{h}{2} + \cos\left(\frac{(I-a)\cdot\pi}{b-a} + \pi\right) & a < I < b \\ h & I \geq b \end{cases} \qquad (5)$$

where $i$ depends on the intensity.

To apply this distance to two colors we compute $I = |I_{\mathbf{c}_1} - I_{\mathbf{c}_2}|/2$ where $I_{\mathbf{c}_1}, I_{\mathbf{c}_2}$ are the intensity component $I$ of the spherical coordinates of the colors $\mathbf{c}_1, \mathbf{c}_2$ and we can express it as $\alpha(\mathbf{c}_1, \mathbf{c}_2)$

# Hybrid Distance

Now we can formulate an hybrid distance between any two colors $\mathbf{c}_1, \mathbf{c}_2$ as follows:

$$d_H(\mathbf{c}_1, \mathbf{c}_2) = (1 - \alpha(\mathbf{c}_1, \mathbf{c}_2)) \cdot d_I(\mathbf{c}_1, \mathbf{c}_2) + \alpha(\mathbf{c}_1, \mathbf{c}_2) \cdot d_C(\mathbf{c}_1, \mathbf{c}_2) \quad (6)$$

where

- $d_I$ is an intensity distance as $d_I(\mathbf{c}_1, \mathbf{c}_2) = |I_{\mathbf{c}_1} - I_{\mathbf{c}_2}|$
- $d_C$ is a chromatic distance as $d_C(\mathbf{c}_1, \mathbf{c}_2) = \sqrt{(\theta_{\mathbf{c}_1} - \theta_{\mathbf{c}_2})^2 + (\phi_{\mathbf{c}_1} - \phi_{\mathbf{c}_2})^2}$.

# Segmentation

- Segmentation is a partition of the image domain set $F$ into connected subsets or regions $(S_1, S_2, ..., S_n)$ such that $\bigcup_{i=1}^{n} S_i = F$ with $\forall i \neq j, S_i \cap S_j = \varnothing$.
- This segmentation method is based is the proposed hybrid distance.
- The algorithm examines all the pixels in sequence, assigning them labels according to the labeling of the pixels in its neighborhood.
- We consider 8-connectivity, so all the operations refer to the pixels' 8-neighborhood $N_8(p)$.

# Segmentation

- Four parameters configure the algorithm behavior.
  - On one hand the distance parameters $a, b, h$ previously explained.
  - On the other hand a threshold $\delta$ to test color similarity.
    - We decide that two colors $\mathbf{c}_1, \mathbf{c}_2$ are equivalent for segmentation purposes if $d_H(\mathbf{c}_1, \mathbf{c}_2) < \delta$.
- We will call nearest neighbors to the subset of $NN(p) \subseteq N_8(p)$ pixels with equivalent colors.

# Experimental Results

- The natural output of a segmentation method is a labels' vector, in this case is a bi-dimensional integer matrix, where each number is linked to a label.
- For a good visual supervision, the output images are drawn using the label's chromaticity and an uniform intensity ($I = 0.7$).

# Experimental Results

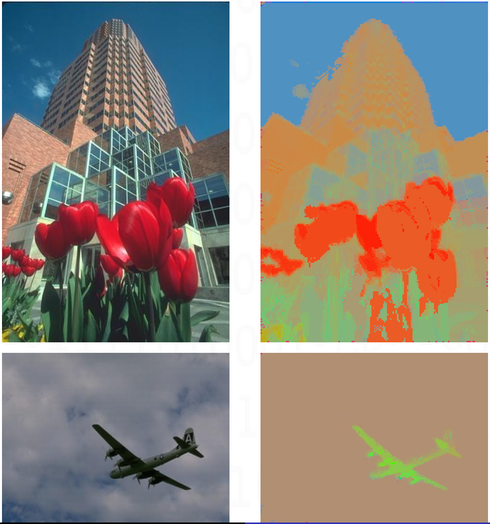
- To validate the proposed segmentation method we will experiment with two different kind of images, on one hand the well-know Berkeley image database.
- And on the other hand a private collection of images taken by the robot NAO .
- The parameter settings for the experiments are: $\delta = 0.02$, $a = 0.2$, $b = 0.4$ and $h = 0.5$

# Experimental Results

- Respect to the first experiment, using the Berkeley database, images are very different each others and we are using the same parameters and as we can see results are goods.

# Experimental Results

# Experimental Results



# Experimental Results

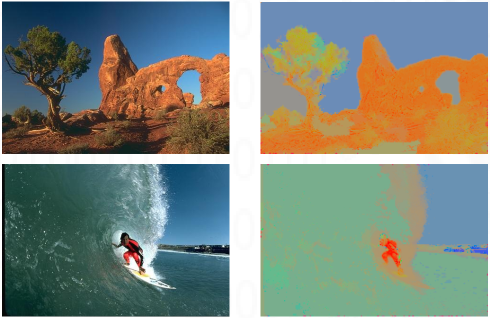


Figure: Experimental results using Berkeley database

# Experimental Results

Respect to the second experiment, images are taken in similar illumination conditions, therefore results are more stable than in the first experiment. It is important to realize the good results avoiding shines and detecting correctly regions with different chromatic properties.

# Experimental Results

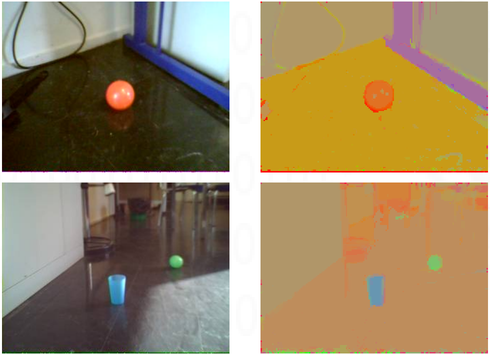


Figure: Robot Images

# Experimental Results

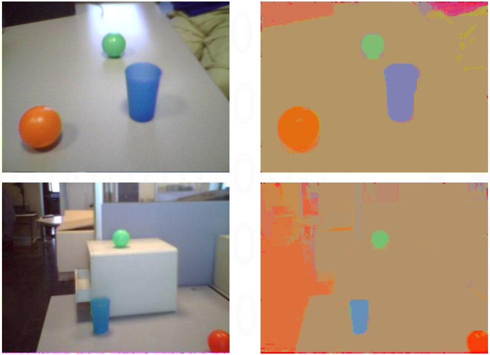


Figure: Robot Images

# Watershed Segmentation

Image segmentation by using watershed

# Fuzzy Watershed Image Segmentation

- Watershed transformation is a powerful mathematical morphology technique for image segmentation.
- The watershed transform considers a bi-dimensional image as a topographic relief map.
- The value of a pixel is interpreted as its elevation.

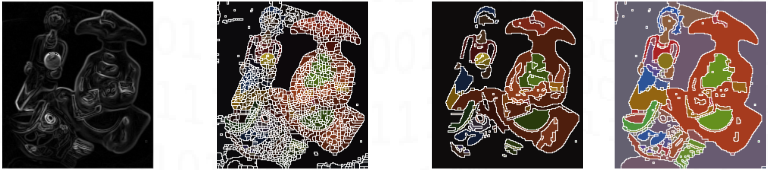
# Fuzzy Watershed Image Segmentation

- The watershed lines divide the image into catchment basins, so that each basin is associated with one local minimum in the topographic relief map.
- The watershed transformation works on the spatial gradient magnitude function of the image.
- The crest lines in the gradient magnitude image correspond to the edges of image objects.

# Experimental results (intensity)

Original image

Gradient | Watershed | Segmentation



(a) (b) (c) (d)

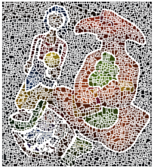
# Experimental results (chromaticity)

Original image

Gradient

(e)

Watershed



(f)

Segmentation

(g)

(h)

# Experimental results (fuzzy)

Original image

Gradient

(i)

Watershed

(j)

Segmentation

(k)

(l)

# From Euclidean to Hyperspherical Coordinates

A pixel $p$ in Euclidean coordinates of $n$ dimensions is expressed by $p = \{v_1, v_2, v_3, ..., v_n\}$ where $v_i$ is the value if the $i - th$ dimension. This pixel can be expressed equivalently by Hyperspherical coordinates as $p = \{l, \phi_1, \phi_2, \phi_3, .., \phi_{n-1}\}$ where $l$ is the vector longitude and $\{\phi_1, \phi_2, \phi_3, .., \phi_{n-1}\}$ are the angular parameters.

# From Euclidean to Hyperspherical Coordinates

This transformation is performed uniquely by,

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

,with this exception, if $v_i \neq 0$ for some$i$ but all of $v_{i+1}, \ldots, v_n$ are zero then $\phi_i = 0$.

# From Euclidean to Hyperspherical Coordinates

Let us denote the hiperspherical transformations of a pixel $p$ as $p = \{l, \bar{\phi}\}$ where $\bar{\phi}$ is the vector of size $n-1$ containing the angular parameters. Applying these definitions in a hyperspectral image we can perform the following separation.

Given a hyperspectral image $\mathbf{I}(x) = \left\{(v_1, v_2, v_3, ..., v_n)_x ; x \in \mathbb{N}^2\right\}$, where $x$ refers to the pixel coordinates in the image domain, we denote the corresponding hyperspherical representation as $\mathbf{P}(x) = \left\{(l, \bar{\phi})_x ; x \in \mathbb{N}^2\right\}$, from which we use $\bar{\phi}_x$ as the chromaticity representation of the pixel's and $l_x$ as its respective intensity.

# E.G.

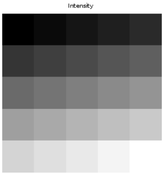
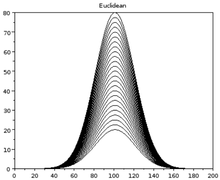
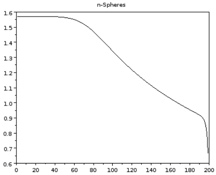



Image intensisty




Euclidean spectra



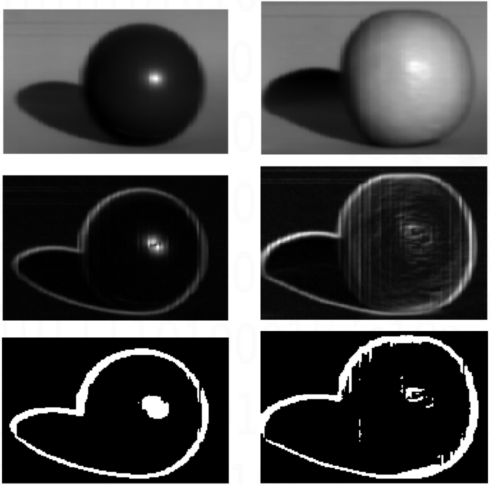

Chromaticity (angular spectra)

# Hyperpspherical Coordinates

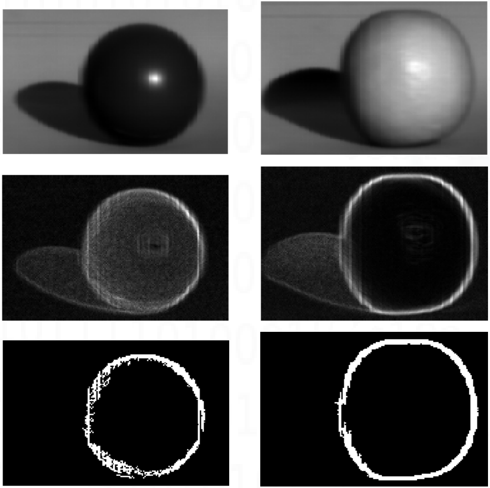
Keep in mind an important difference between the Euclidean and Hyperspherical representations. When working with the Euclidean representation, a pixel is represented by a "point" in the $n$-th space. When working in Hyperspherical representation, $\bar{\phi}$ is a "line" the $n$-th space. $I$ contains the intensity or vector magnitude.

Accordingly with the aforegoing transformation, we can perform the following hyperspectral separation. Given a image $\mathbf{I}(x) = \left\{(v_1, v_2, v_3, \ldots, v_n)_x ; x \in \mathbb{N}^2\right\}$ in the traditional Euclidean representation we can obtain the equivalent image $\mathbf{P}(x) = \left\{(I, \bar{\phi})_x ; x \in \mathbb{N}^2\right\}$ and from $\mathbf{P}(x)$ we can separate $\mathbf{II}(x) = \left\{(I)_x ; x \in \mathbb{N}^2\right\}$ as the image intensity, and $\mathbf{C}(x) = \left\{(\bar{\phi})_x ; x \in \mathbb{N}^2\right\}$ as the image chromaticity.

# Traditional Gradient



# Chromatic Gradient



# Chromatic Gradient

Figure: Chromatic gradient applied on heterogeneous images. Second

# Hybrid Gradient

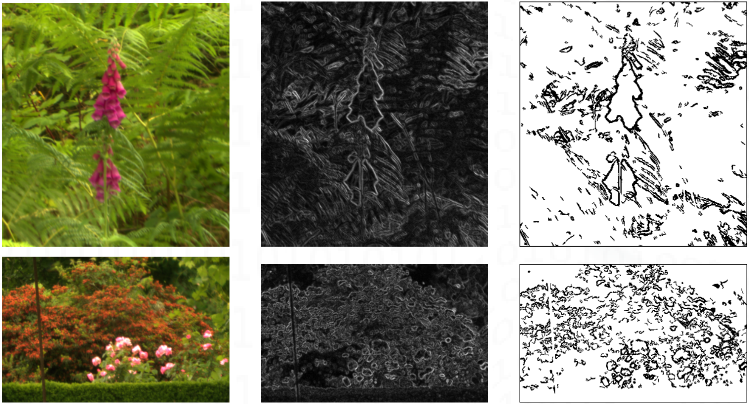


Figure: Hybrid gradient on hyperspectral images

# Hybrid Gradient

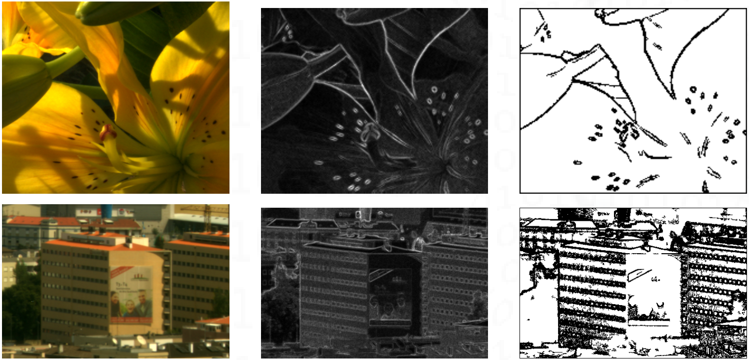


Figure: Hybrid gradient on hyperspectral images

# Hybrid Gradient

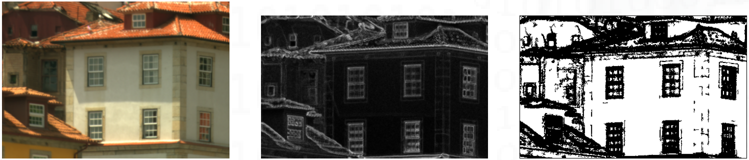
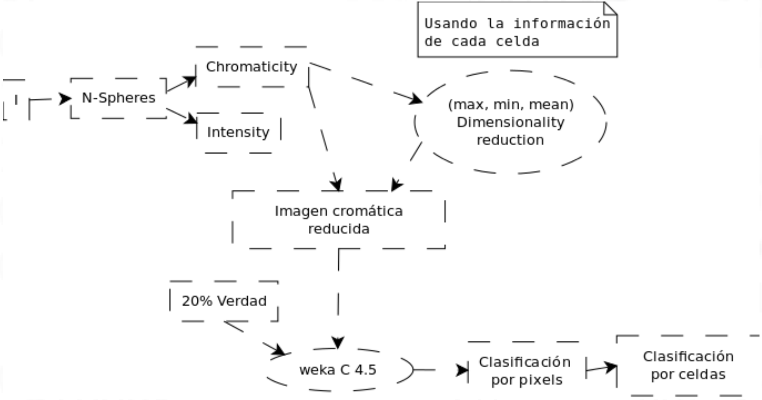
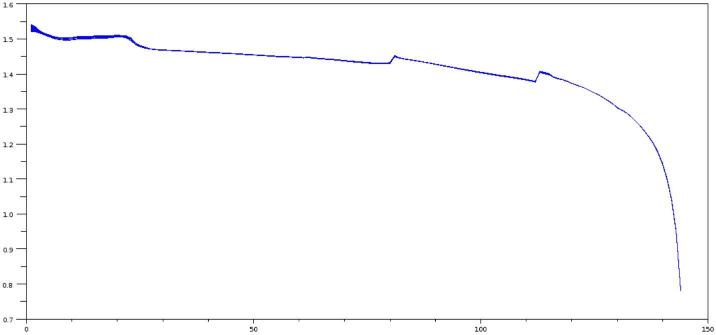


Figure: Hybrid gradient on hyperspectral images

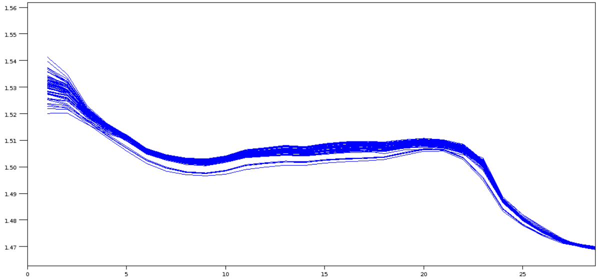
# Schema


Usando la información de cada celda
N-Spheres
Chromaticity
Intensity
(max, min, mean) Dimensionality reduction
Imagen cromática reducida
20% Verdad
weka C 4.5
Clasificación por pixels
Clasificación por celdas

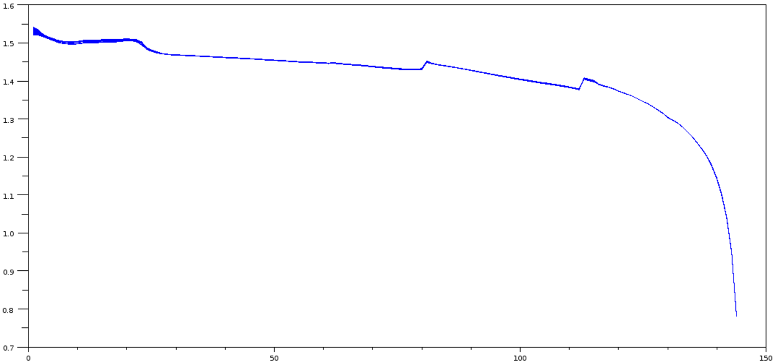
# Chromatic Spectra



# Schromatic spectra II



# Dimensionality Reduction



# Dimensionality reduction

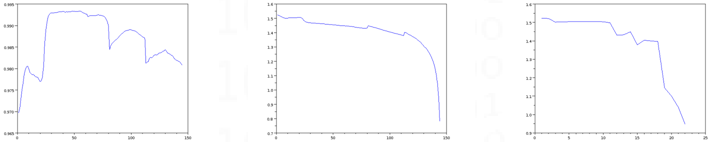
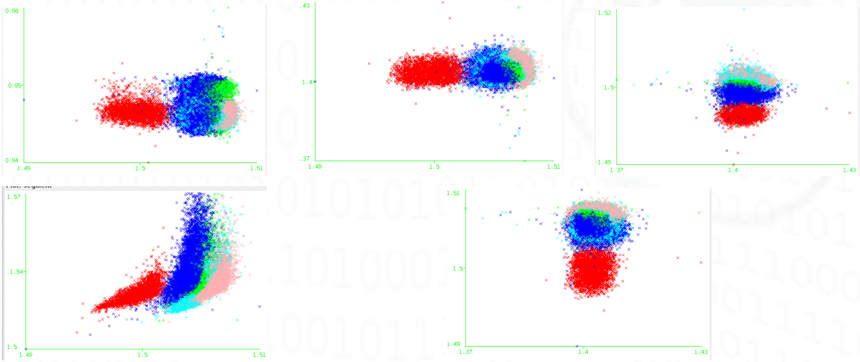
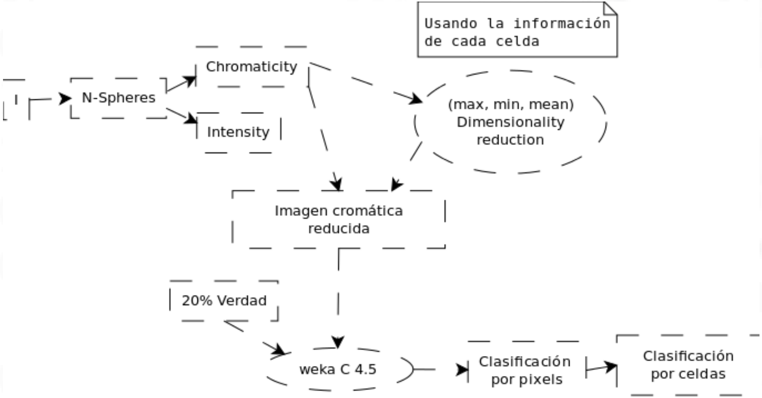



Figure: Euclidea, Cromática y cromática reducida

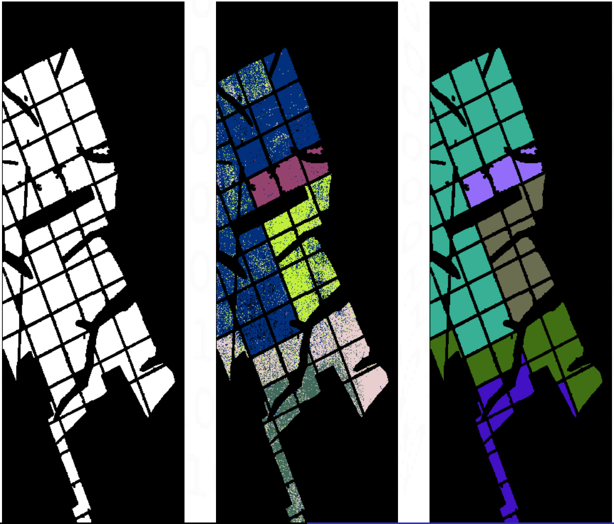
# Spatial distribution



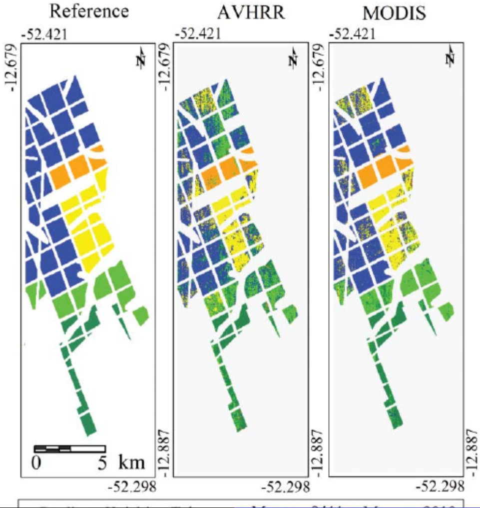
# Schema


Usando la información
de cada celda
N-Spheres
Chromaticity
Intensity
(max, min, mean)
Dimensionality
reduction
Imagen cromática
reducida
20% Verdad
weka C 4.5
Clasificación
por pixels
Clasificación
por celdas

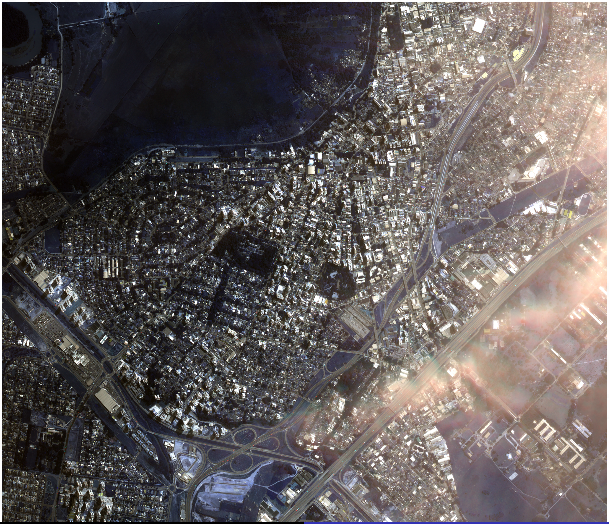
# by C 4.5



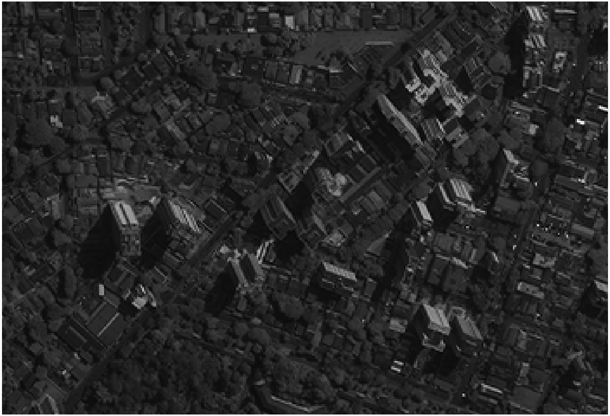
# Versus


Reference
AVHRR
MODIS
-52.421
-52.421
-52.421
-12.679
-12.679
-12.679
0
5 km
-12.887
-12.887
-12.887
-52.298
-52.298
-52.298

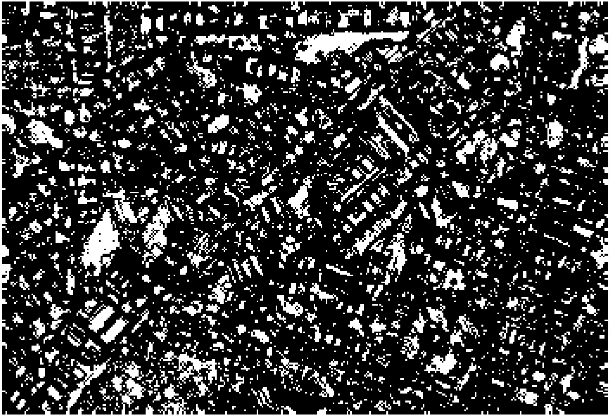
# SJC y nubes



# Region 1

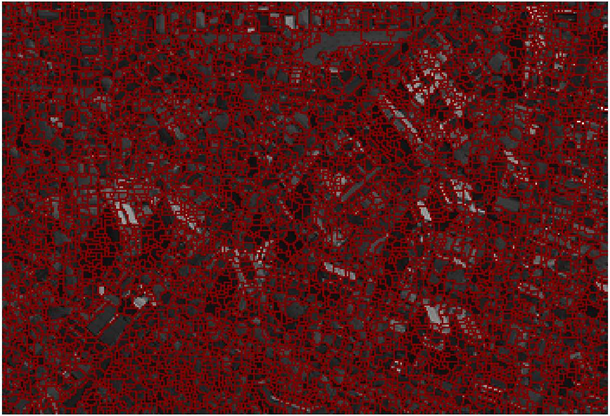


# Region 1 Gradiente 1

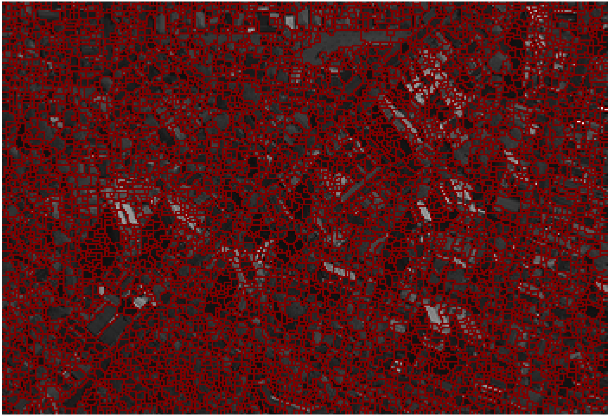


# Region 1 Gradiente 2

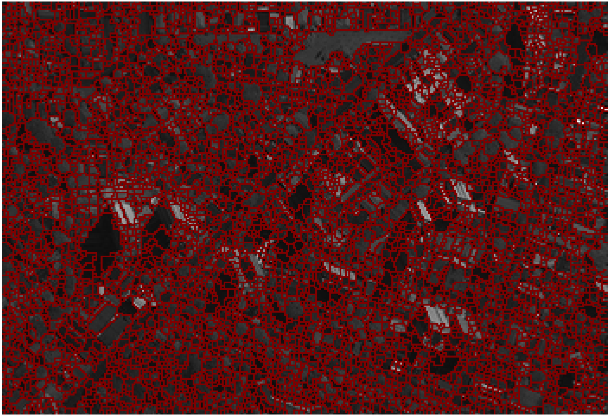
# Region 1 Watershed 1



# Region 1 Watershed 2

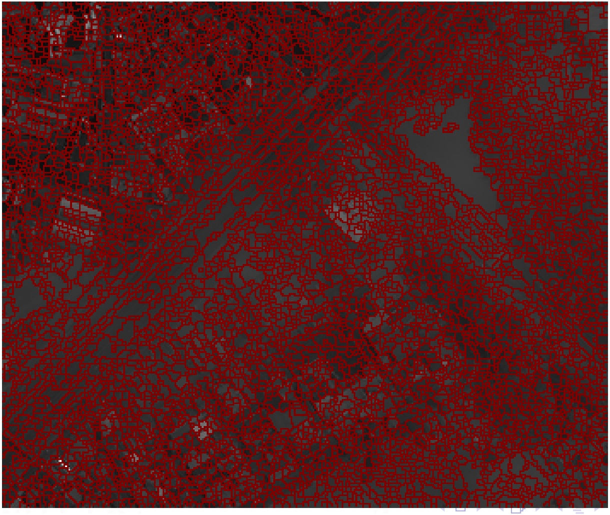


# Region 1 Watershed 3

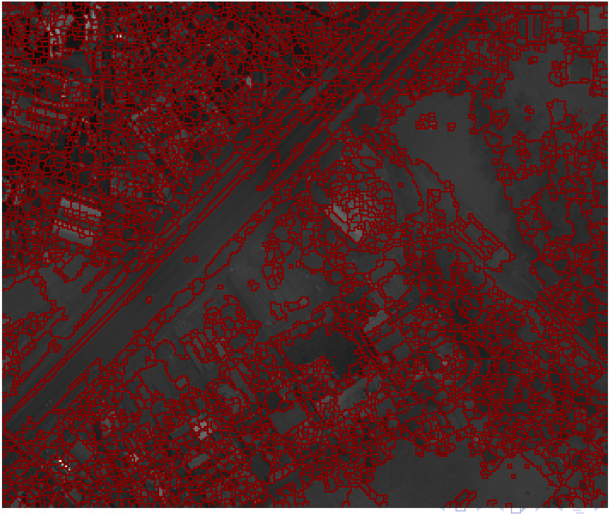


# Region 2

# Region 2 Watershed 1

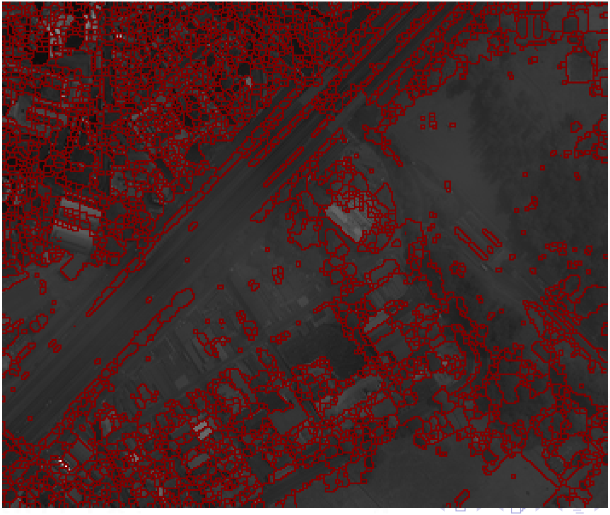


# Region 2 Watershed 2



# Region 2 Watershed 2

# Region 2 Watershed 3



Muito obrigado,
Eskerrik asko.