2 Image segmentation

1. Definitions, representation and evaluation results
2. Region based methods
3. Clustering based methods
4. Other methods
5. Actual methods

Last week (1,2,3): introduction and simple methods

Today (4,5): we will see more complex methods!

2 Image segmentation

Review activity

- Drawbacks for the Region Growing, Split & Merge and K-means

2 Image segmentation

Review activity

RG: dependent on seed placement
RG: noisy images A4 A8
RG: criterion aggreg
S&M: artefacts squared results
S&M: criterion merging / Splitting
S&M: computational time (merging)
K-means: feature space
K-means: Nº clusters
K-means: data distribution

2 Image segmentation

RG: dependent of initial seed
RG: number of seeds?
RG: criterion definition: threshold
RG: refine results: A4, A8
S&M, RG: Computational cost
S&M: pixelated results
S&M: definition of criterions Split & Merge
S&M: merge step (cost)
Kmeans: number of clusters?
Kmeans: feature selection
Kmeans: spatial information?

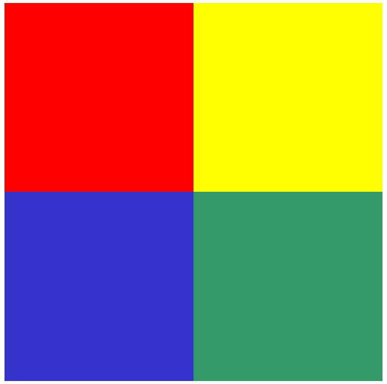
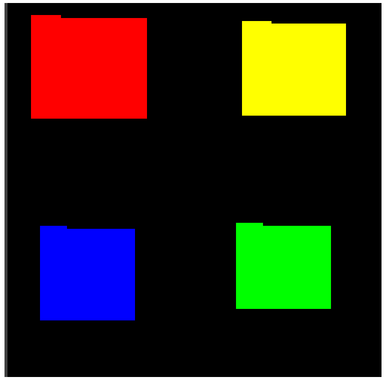
2 Image segmentation

Review activity

- List of improvements (Region Growing)
  - Active regions
  - Seed placement
  - Multiresolution
  - Criterion function
  - Contour information
  - …

2 Image segmentation
2.2 Region based methods

ACTIVE REGIONS: Regions “are moving” around the image (adding and removing pixels) with the goal to improve a global result.

Energy function

Include the desired properties of the global image segmentation.

2 Image segmentation
2.2 Active regions

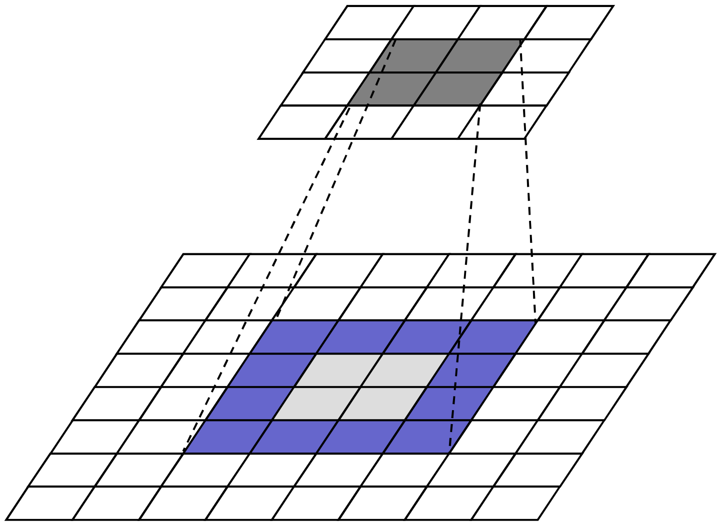
Optimize

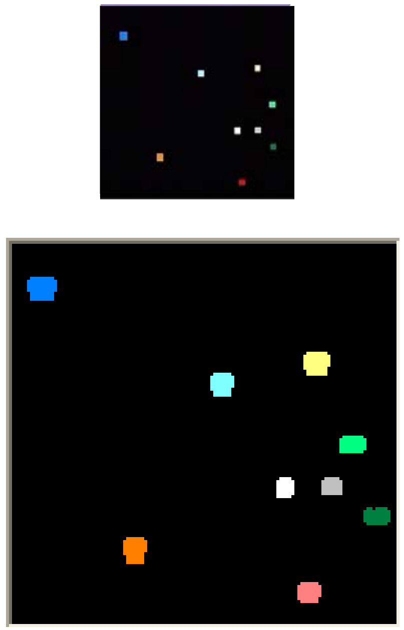
The energy function is optimized using a search algorithm, like the Region Competition: regions compete for pixels trying to minimise the energy of the segmentation

2 Image segmentation
2.2 Multiresolution

The idea is to build a piramide of images, where the images of low spatial resolution are segmented first, and the results are refined progressively (act as initial result)

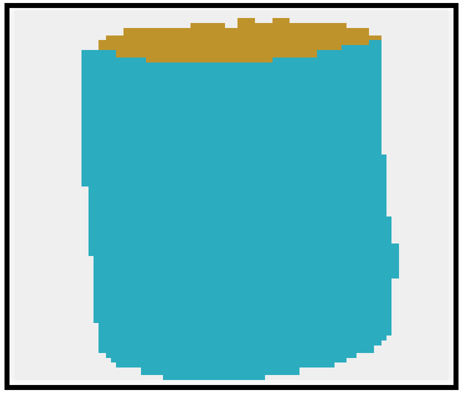
Robust to noise





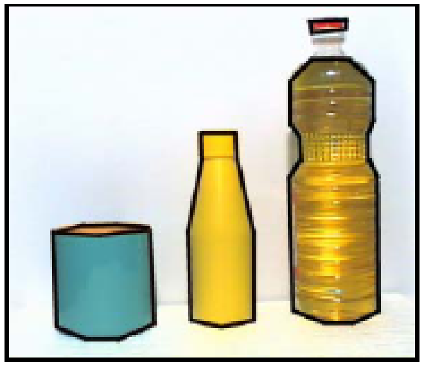
2 Image segmentation
2.5 Other methods:Region-based

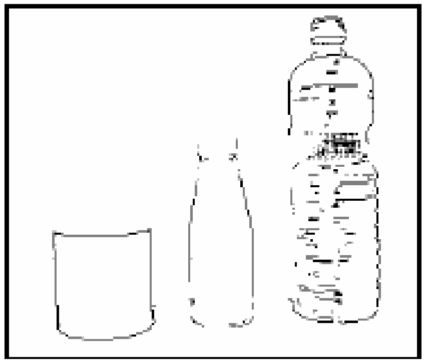
Positive	Negative
- Well defined regions.	- Choice of growing criterion.
- Closed contours.	- Choice of starting seed point.
	- Inaccurate boundaries.



2 Image segmentation
2.5 Other methods: Boundary-based

Positive	Negative
- Accurate boundaries. - Fine edges.	- Sporious and broken edges.





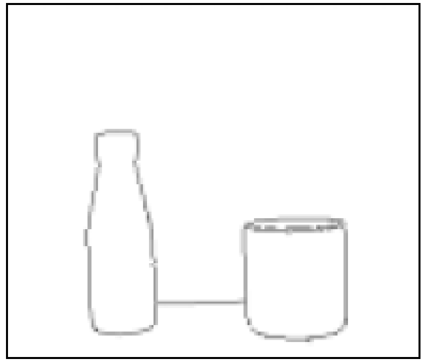
2 Image segmentation
2.5 Other methods: Boundary-based

First, we need a contour extraction

Sobel

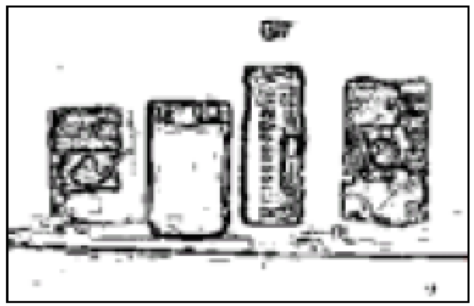
-1	-2	-1
0	0	0
1	2	1

-1	0	1
-2	0	2
-1	0	1



- Noisy contours
- Open contours

- Contour refinement
- Contour union



Original image

Contour extraction

2 Image segmentation
2.5 Other methods

Image segmentation integrating color, texture and boundary information

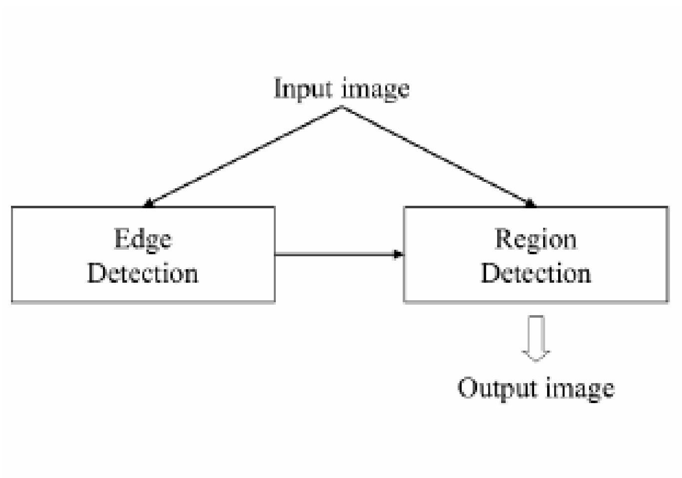
Xavier Muñoz

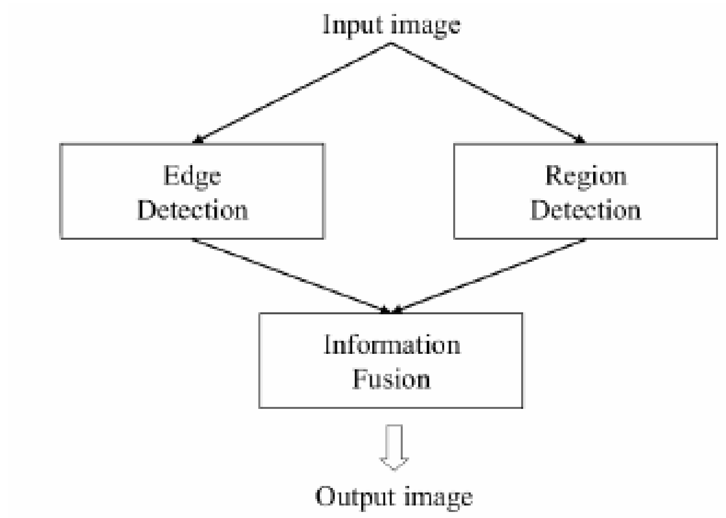
PhD Thesis

See Freixenet et al. ECCV 2004 paper as additional reading

2 Image segmentation
2.5 Combining methods

Time of the fusion

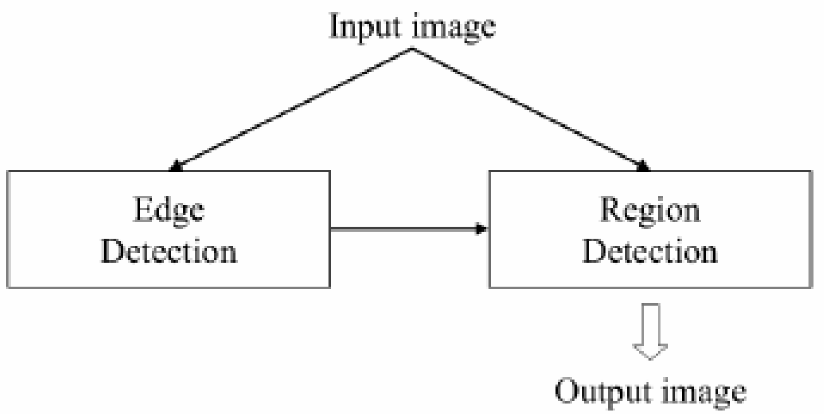




Embedded Post-processing

2 Image segmentation
2.5 Combining methods

Edge information is used inside a region segmentation algorithm.



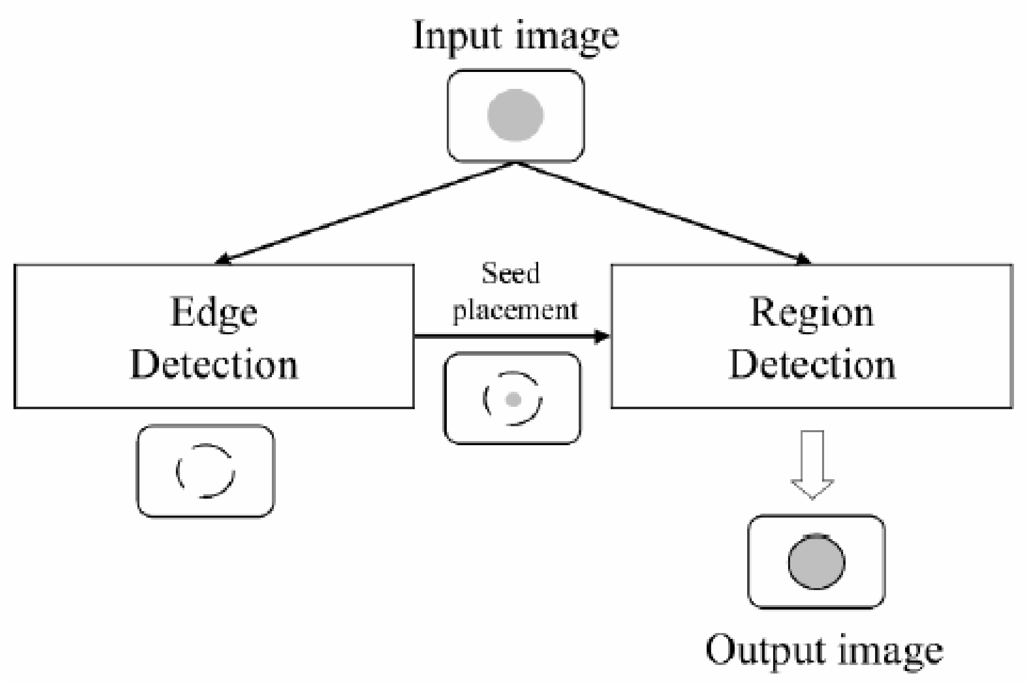
a) Seed Placement Guidance

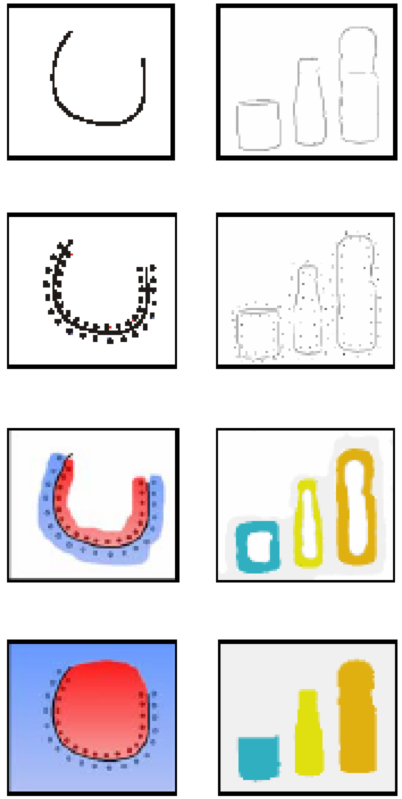
b) Control of Decision Criterion

2 Image segmentation
2.5 Combining methods

a) Seed Placement Guidance

Edge information is used to decide which is the most appropriate position to place the seed.

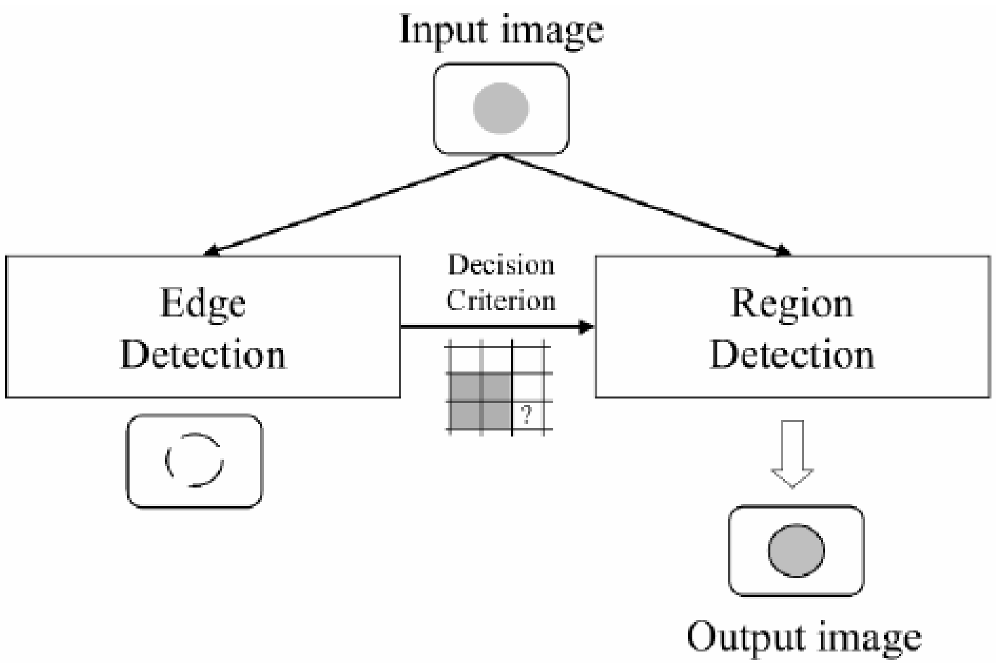


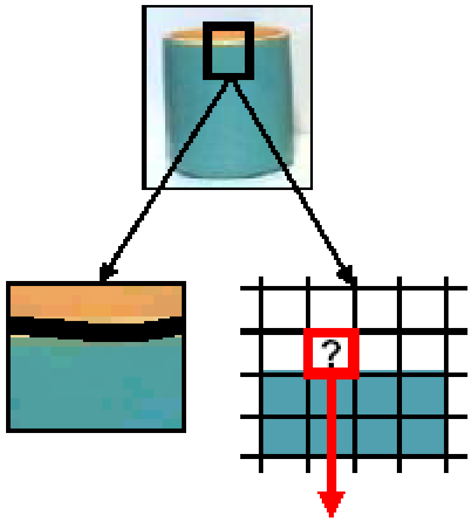


2 Image segmentation
2.5 Combining methods

b) Control of Decision Criterion

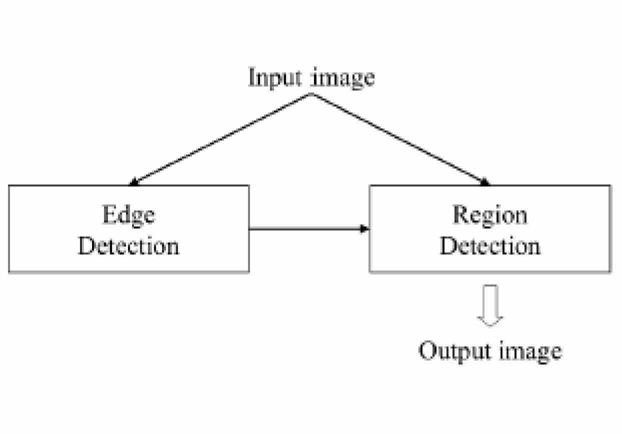
Edge information is included in the definition of the decision criterion which controls the growth of the region.

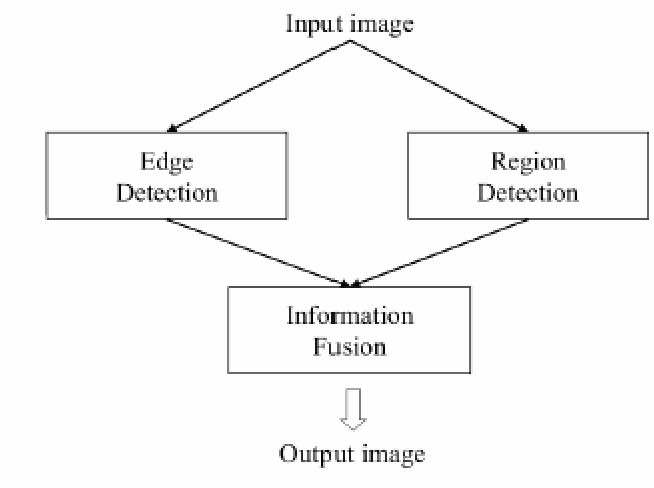




2 Image segmentation
2.5 Combining methods

Time of the fusion

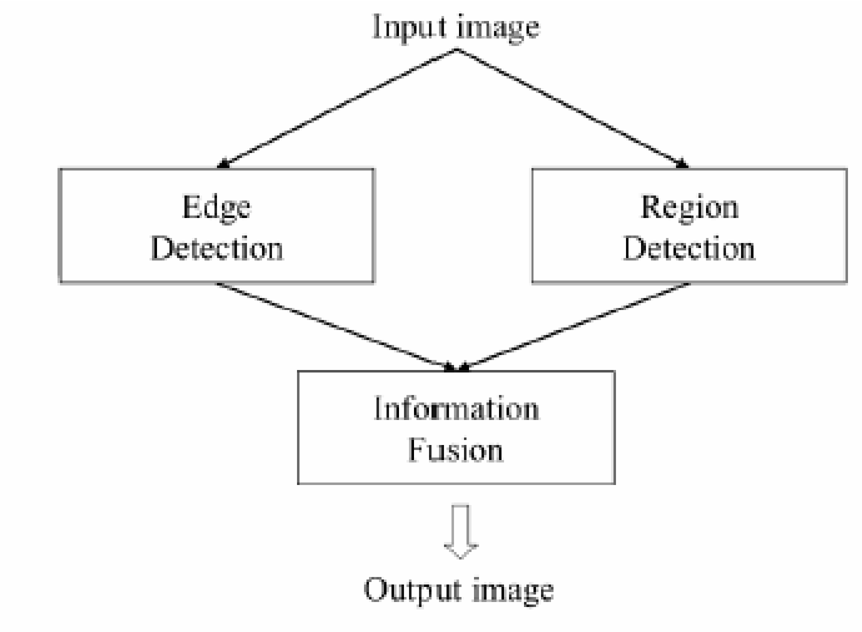




Post-processing

2 Image segmentation
2.5 Combining methods

Edge and region information are independently extracted, and then integrated together.



a) Over-segmentation

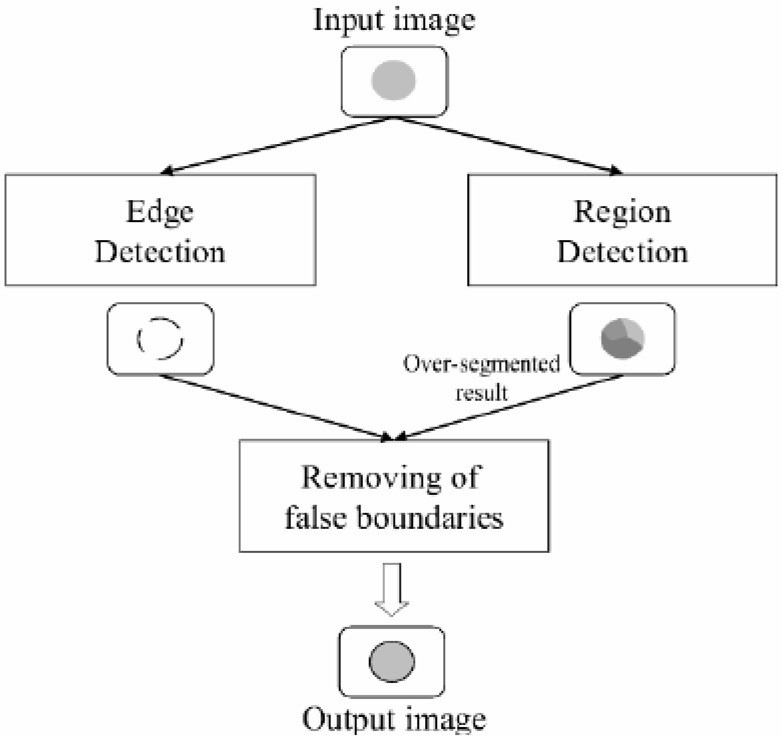
b) Boundary Refinement

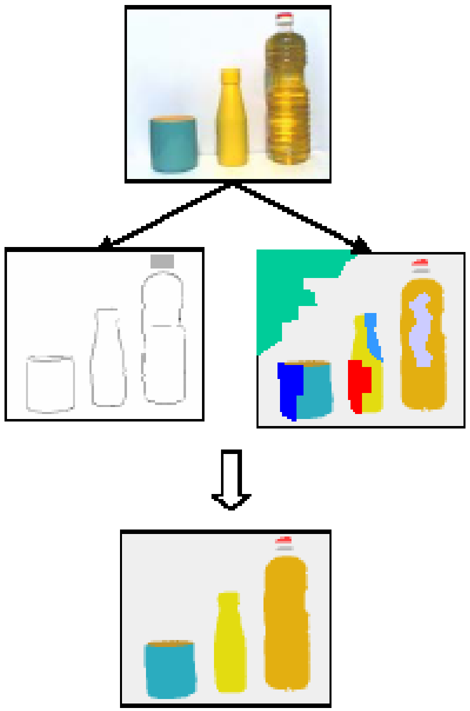
c) Selection-Evaluation

2 Image segmentation
2.5 Combining methods

a) Over-segmentation

Each boundary of an over-segmented result is checked to know if it is coherent in the dual approach.

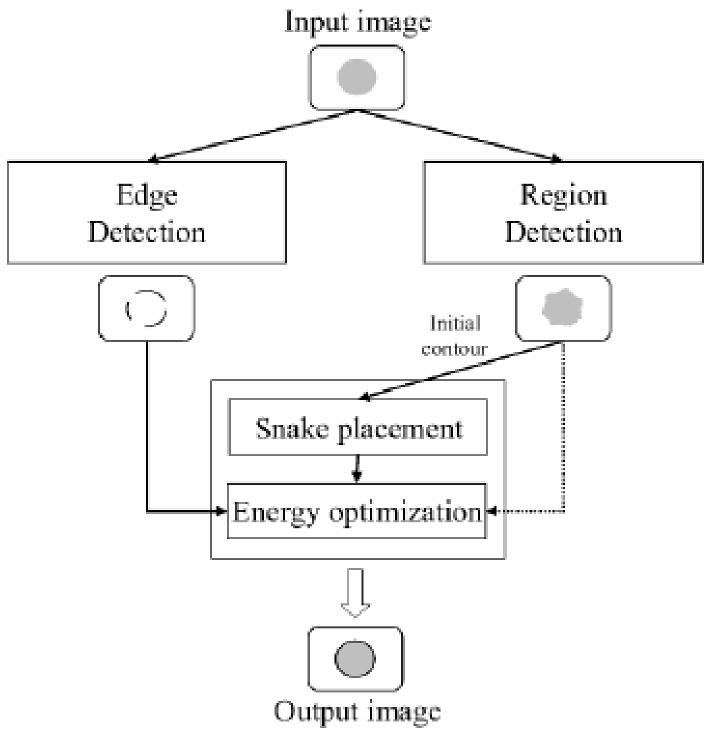


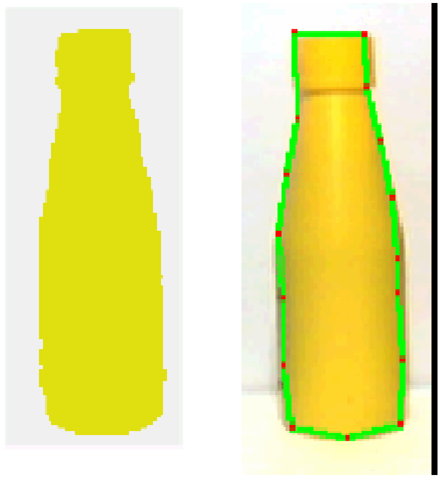


2 Image segmentation
2.5 Combining methods

b) Boundary Refinement

Region-based segmentation is a first approximation to the final segmentation. Edge information allows to refine the region

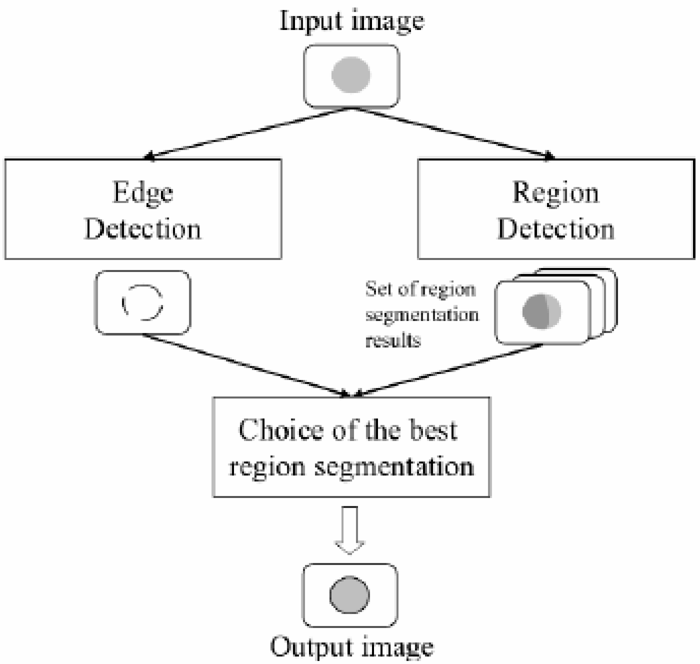


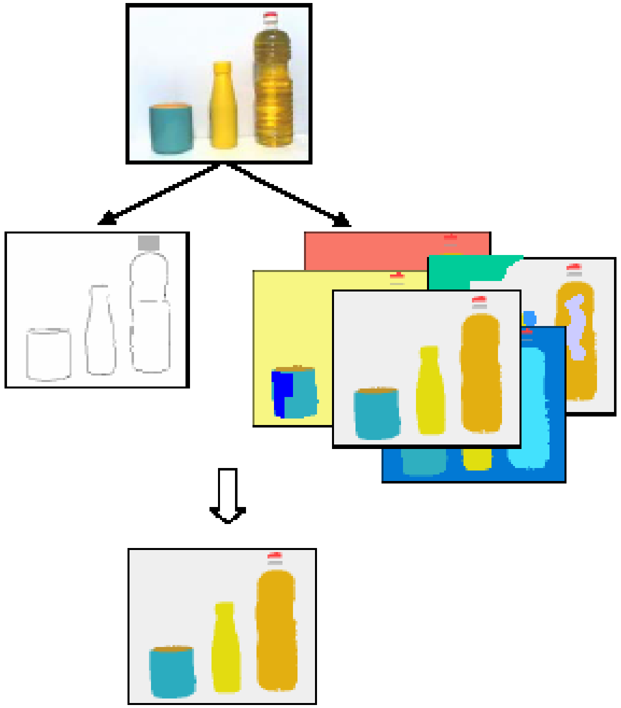


2 Image segmentation
2.5 Combining methods

c) Selection-Evaluation

Edge information allows to evaluate the quality of different region-based segmentation results, with the aim of choosing the best.





2 Image segmentation
2.5 Combining methods

Conclusions:

Embedded	Post-processing
- 1 “superior” algorithm.	- n simple algorithms.
- **Goal:** avoidance of errors.	- **Goal:** correction of errors.
- Complexity ⇧	- Needs good initial segmentation results.
- Independency ⇩	

2 Image segmentation

More information at: Berkeley University
http://www.cs.berkeley.edu/projects/vision/grouping/

Graph based image segmentation :

Shi &Malik. Normalized cuts and image segmentation. PAMI 22(8) 2000

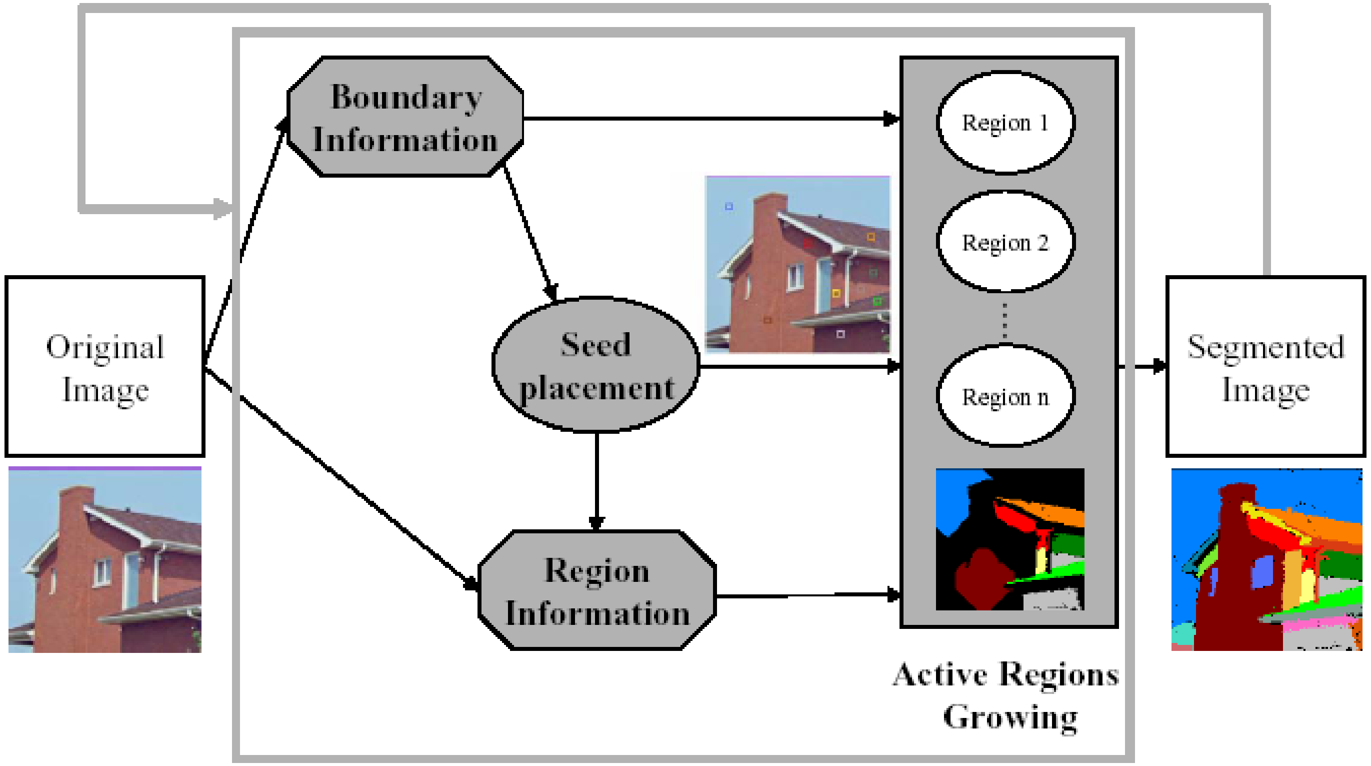
Depuis & Vasseur. Image segmentation by cue selection and integration. IVC 24 2006.

J. Freixenet, X. Muñoz, J. Martí, X. Lladó. Colour Texture Segmentation by Region-Boundary Co-operation. ECCV 2004

2 Image segmentation
2.5 Combining methods

New proposal combining:

- **Seed placement guidance**
- **Control of decision criterion**
- **Boundary refinement**



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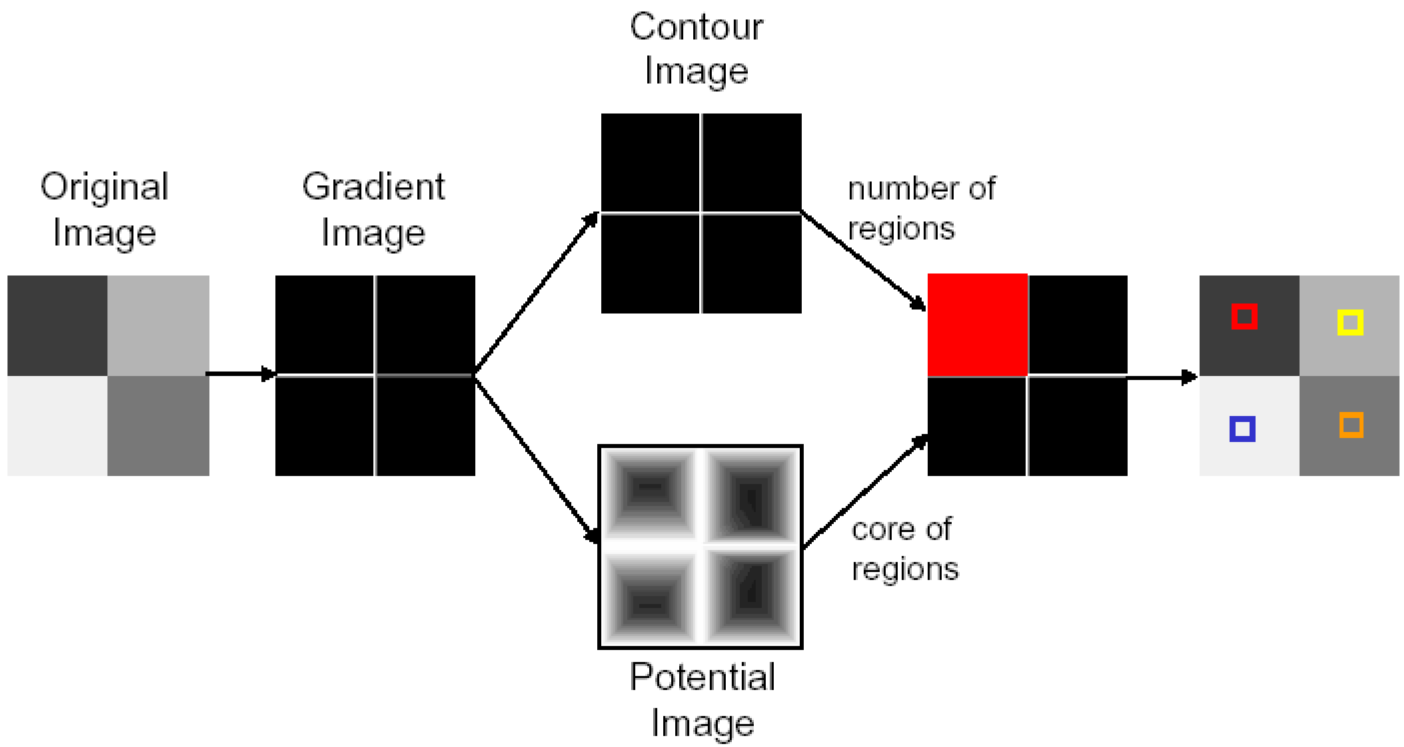
2 Image segmentation
2.5 Combining methods

2 Image segmentation
2.5 Combining methods

To model the region an initial seed has to be placed inside the region.

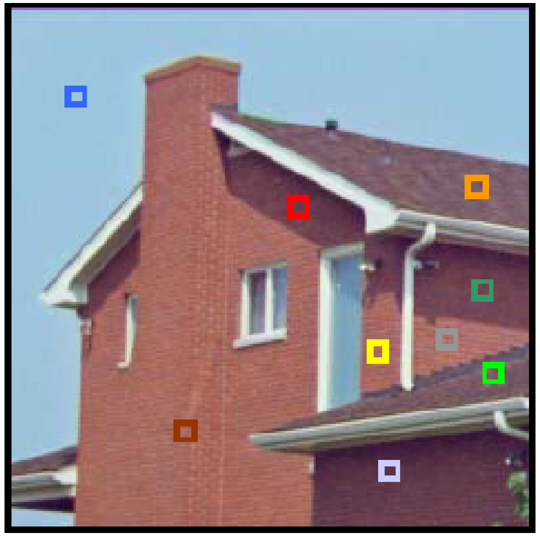
→ Core of the region (furthest away from boundary).

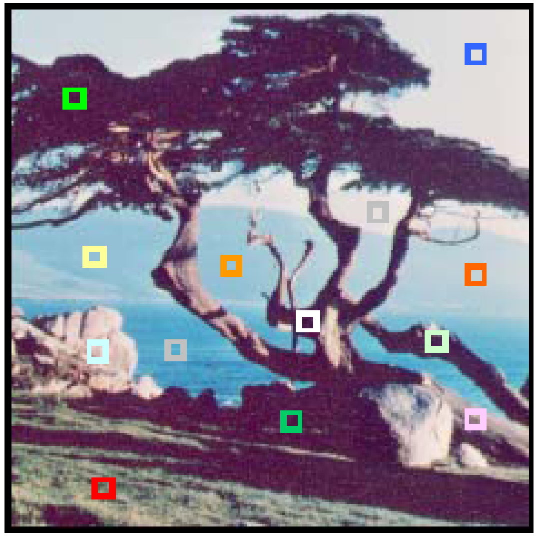


2 Image segmentation
2.5 Combining methods

Seeds are placed completely inside identified regions.

Not always all regions are detected.

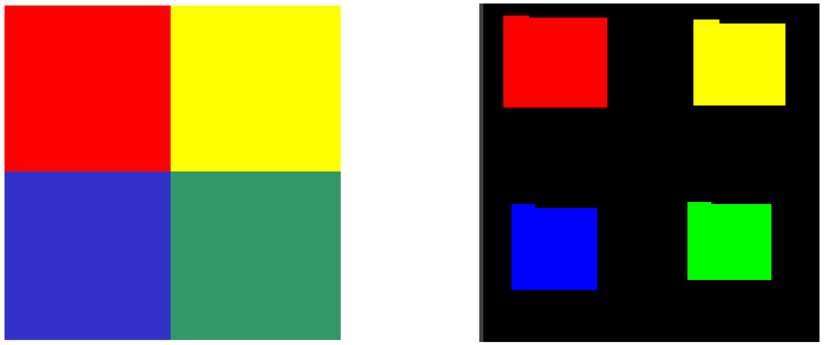




2 Image segmentation
2.5 Combining methods

Active Region

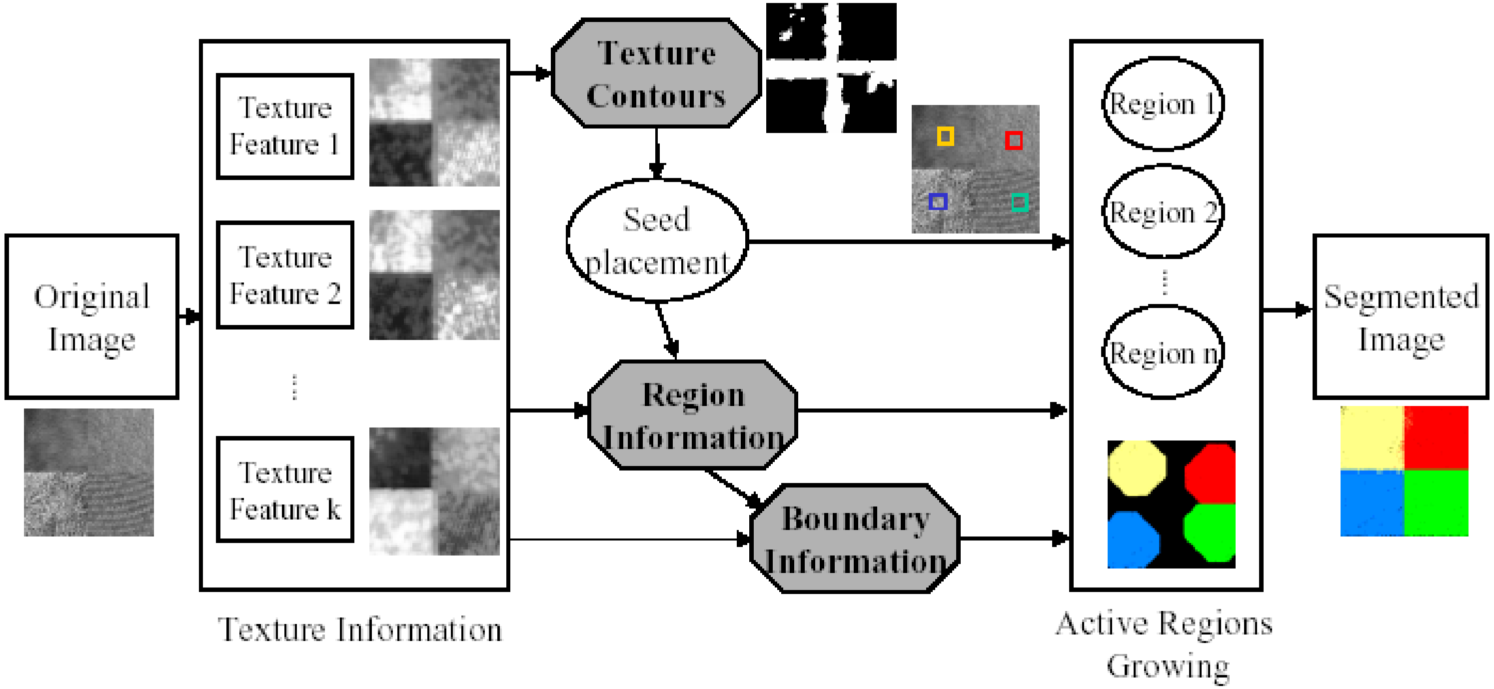
It incorporates region-based information on the classic active contour model.



The region moves trough the image (shrinking or expanding) in order to contain a single, whole region.

2 Image segmentation
2.5 Combining methods

The extension to texture segmentation is performed by considering texture features as the source of our segmentation strategy.



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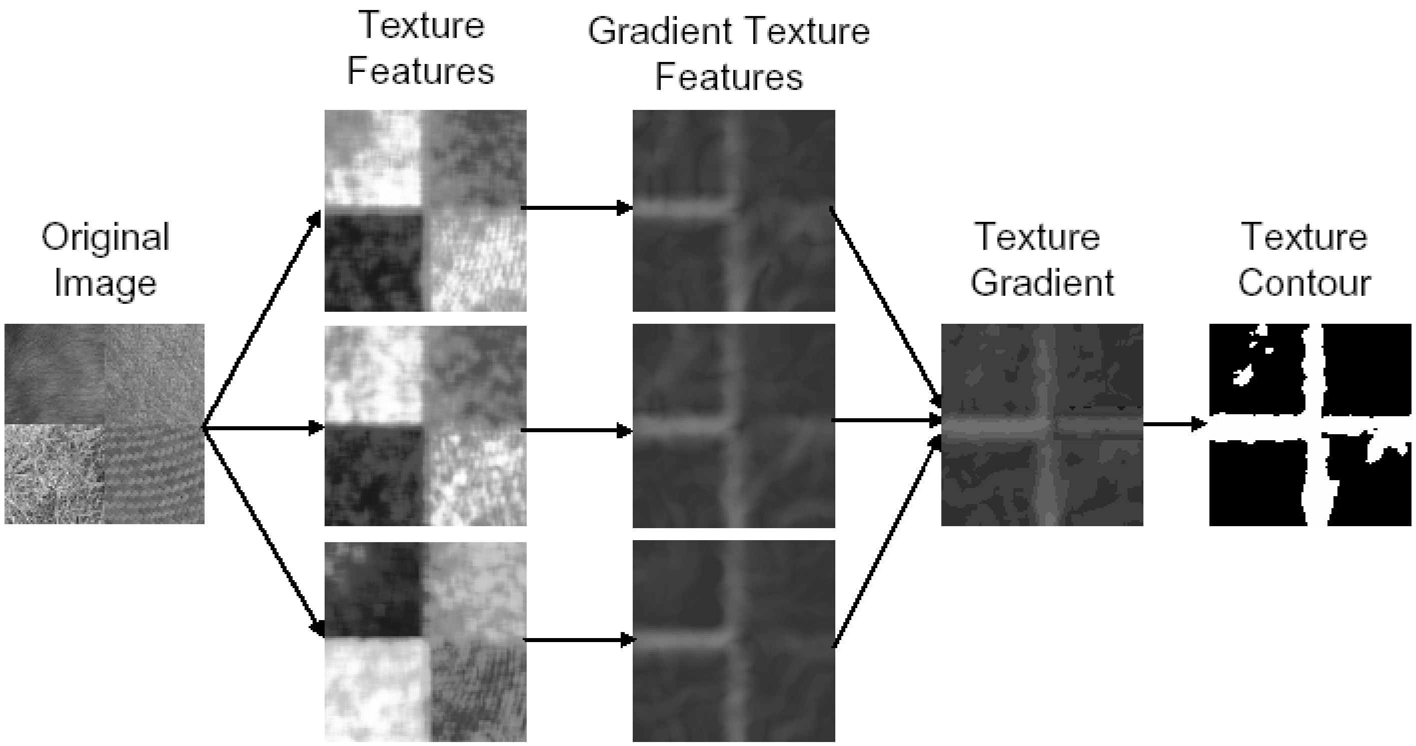
2 Image segmentation
2.5 Combining methods

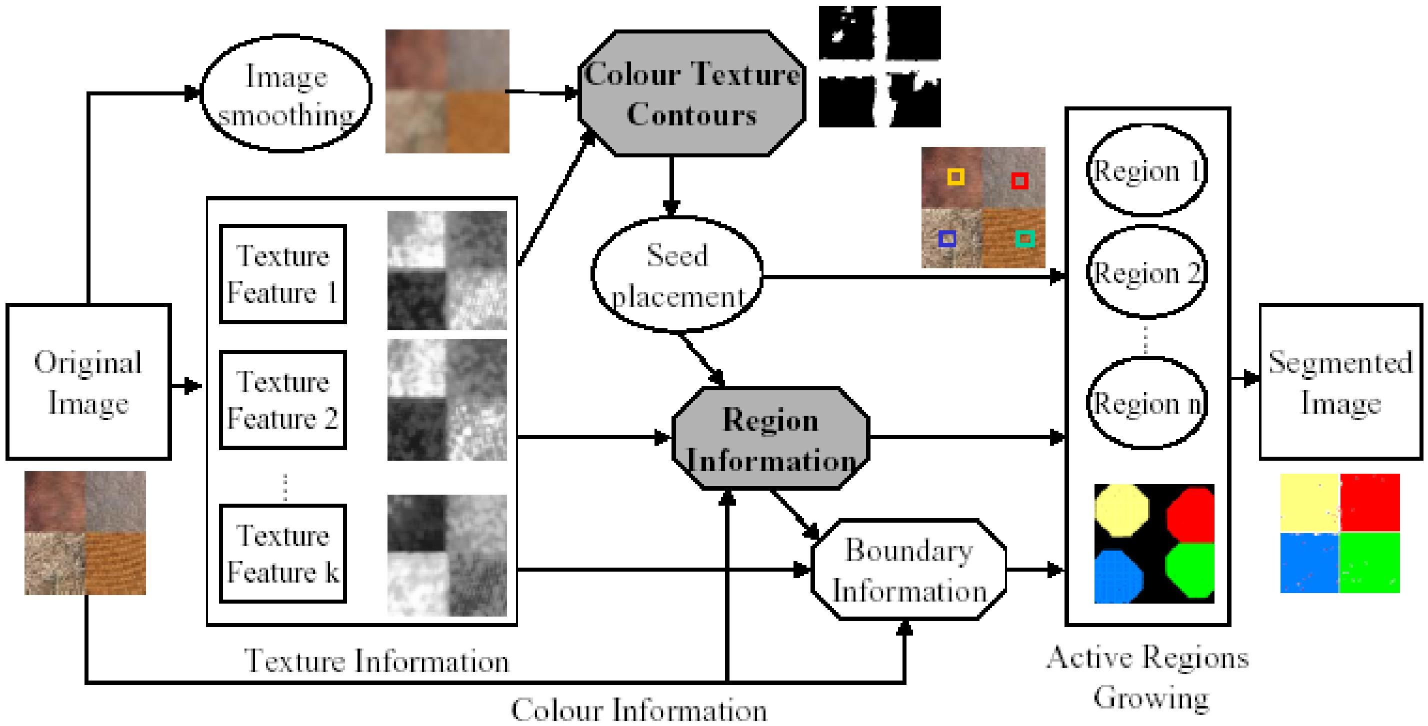
Texture Contours

Texture edge detection is considered as a classical edge detection scheme in the multidimensional set of *k* texture features.



2 Image segmentation
2.5 Combining methods

The inclusion of colour-texture information involves two major issues:
- **Extraction of perceptual edges**
- **Modelling of colour texture**



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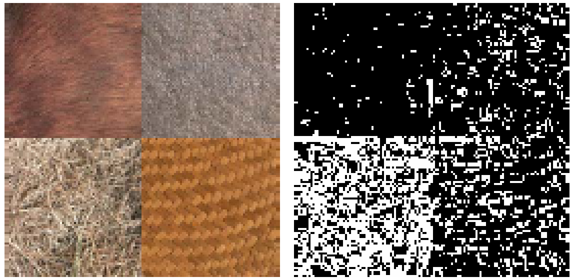
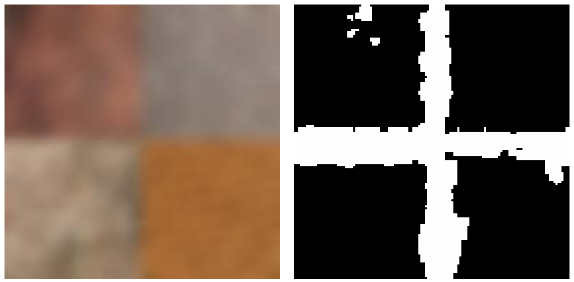
2 Image segmentation
2.5 Combining methods

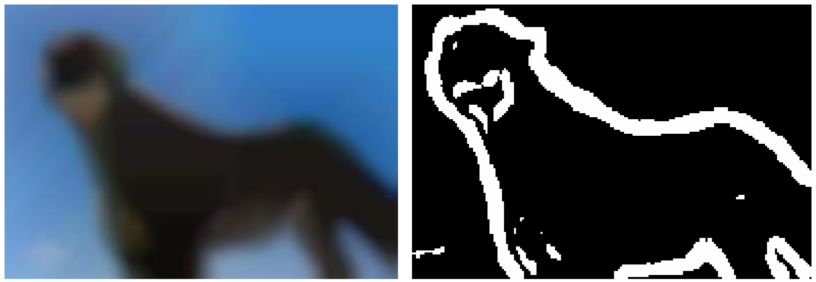
Perceptual Edges

Texture edges + $\boxed{\text{colour edges}}$

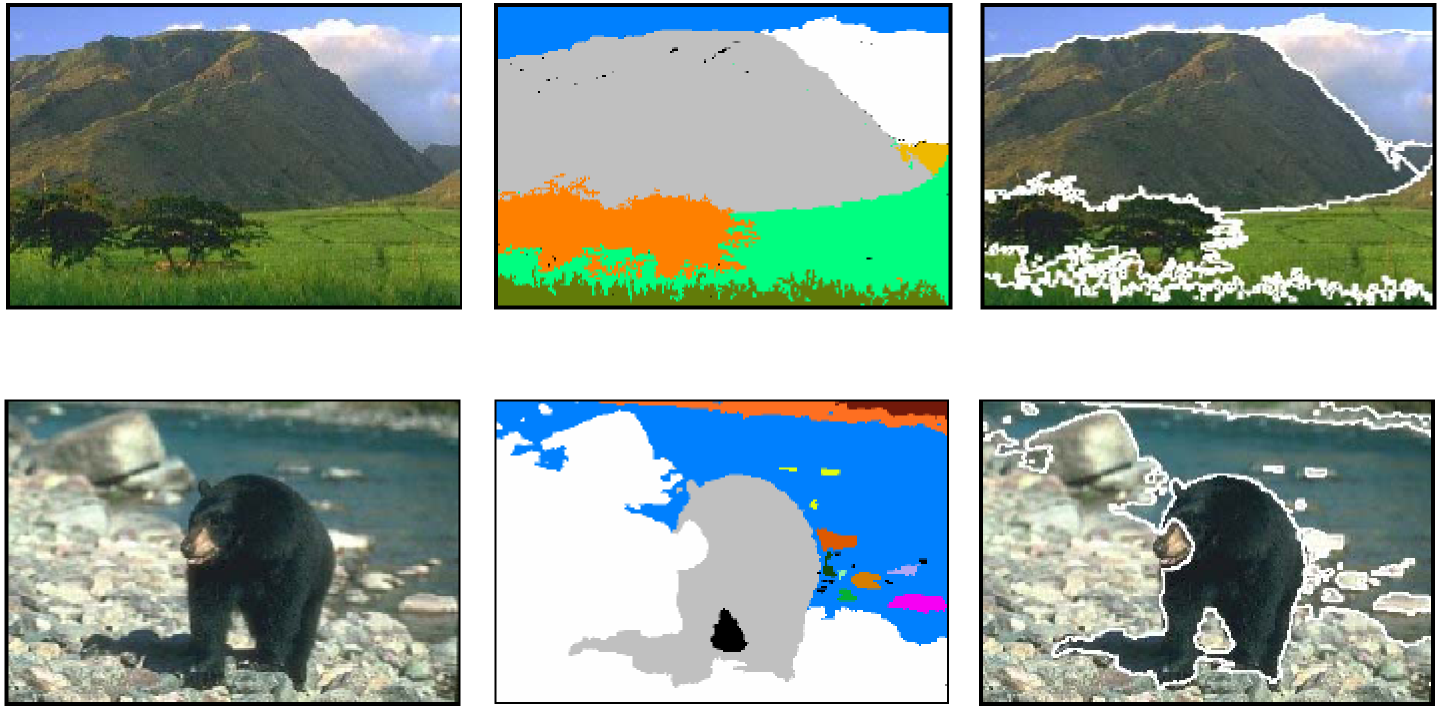


Textures look homogeneous when are seen from far away.



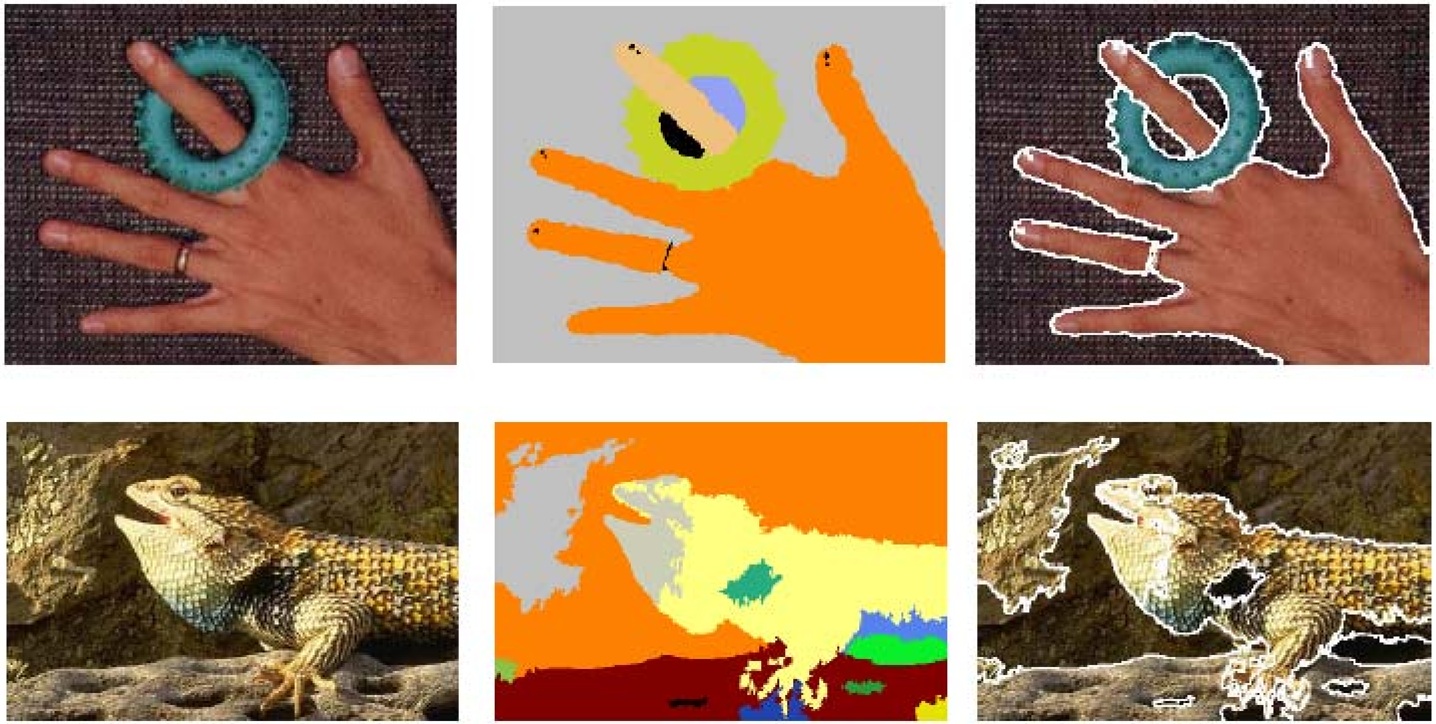


Real Images



2 Image segmentation
2.5 Combining methods

Real Images



2 Image segmentation

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2 Image segmentation

1. Definitions, representation and evaluation results
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5. Actual methods

2.6 Normalized Cuts

2.7 Mean Shift

PRESENTATION

Normalized cuts

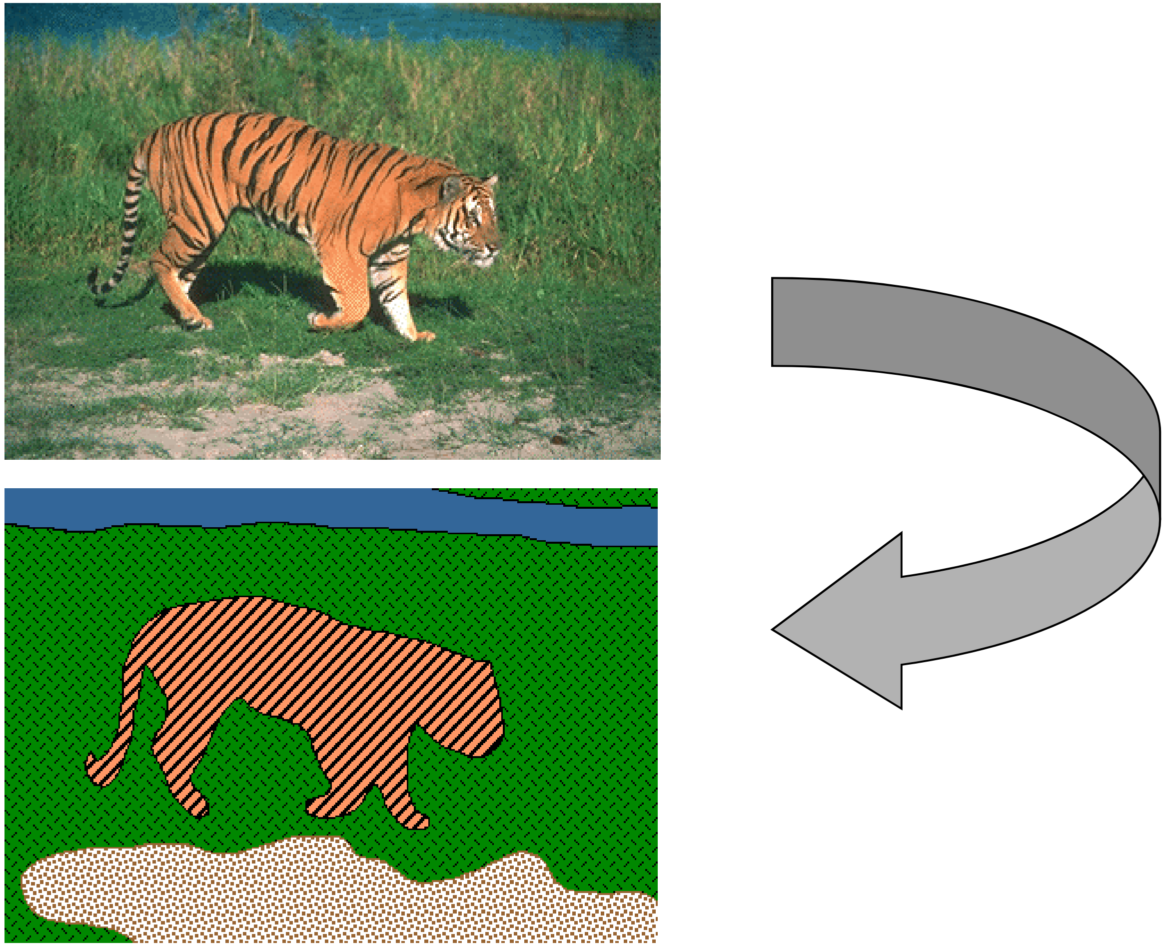
Ismael Garcia
Eloi Colomeda

Normalized Cuts.

Scene Segmentation and Interpretation

Stephen Thomas
Luis Alfredo Mateos

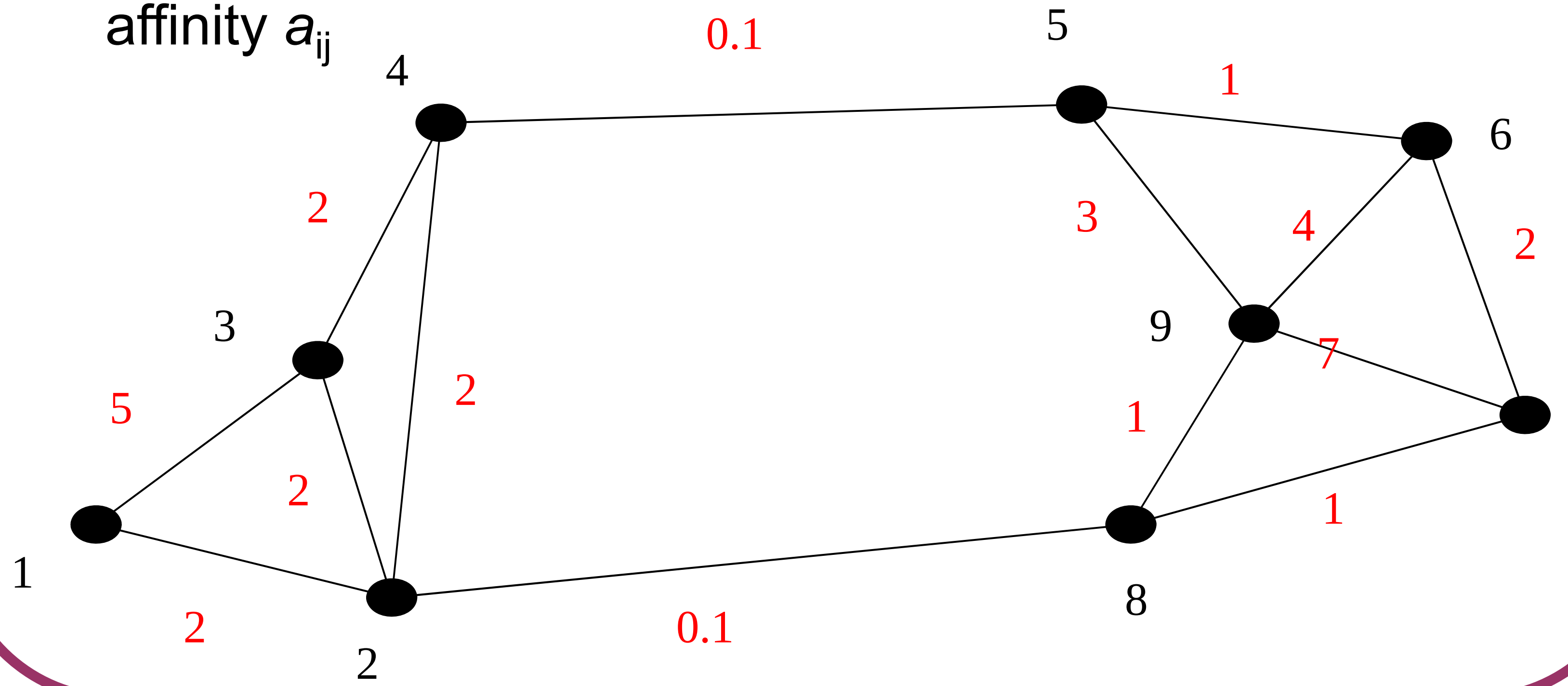
2 Image segmentation
2.6 Normalized cuts



2 Image segmentation
2.6 Normalized cuts

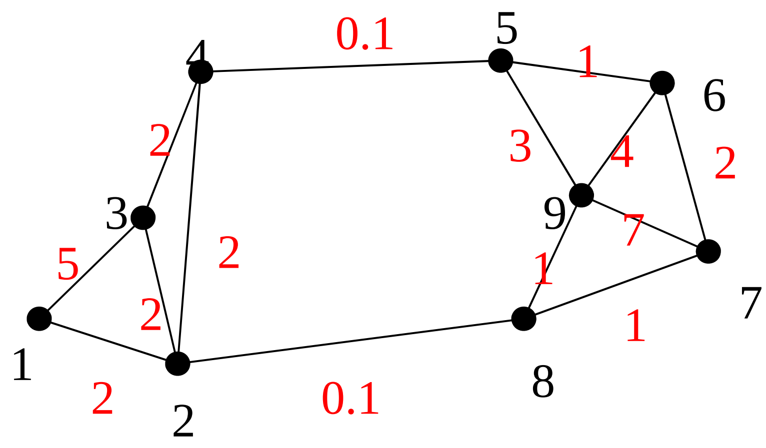
Segmentation as a **graph** problem: $G = (V,E)$

- V is set of features $\{\mathbf{x}_i\}$
- E is set of connections between features weighted by affinity a_{ij}



2 Image segmentation
2.6 Normalized cuts

Graph as a **matrices**



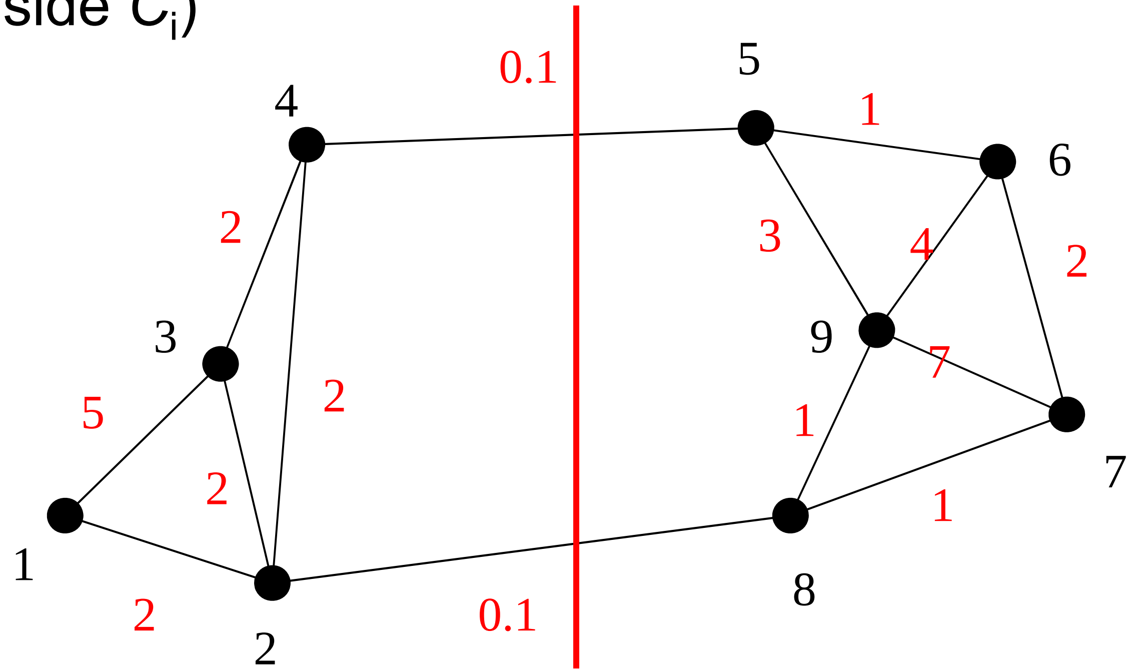
$$A=\begin{bmatrix} 0 & 2 & 5 & 0 & 0 & 0 & 0 & 0 & 0 \\ 2 & 0 & 2 & 2 & 0 & 0 & 0 & .1 & 0 \\ 5 & 2 & 0 & 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 2 & 2 & 0 & 0.1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.1 & 0 & 1 & 0 & 0 & 3 \\ 0 & 0 & 0 & 0 & 1 & 0 & 2 & 0 & 4 \\ 0 & 0 & 0 & 0 & 0 & 2 & 0 & 1 & 7 \\ 0 & 0.1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 3 & 4 & 7 & 1 & 0 \end{bmatrix}$$

(Sometimes called an ***affinity matrix****)*

2 Image segmentation
2.6 Normalized cuts

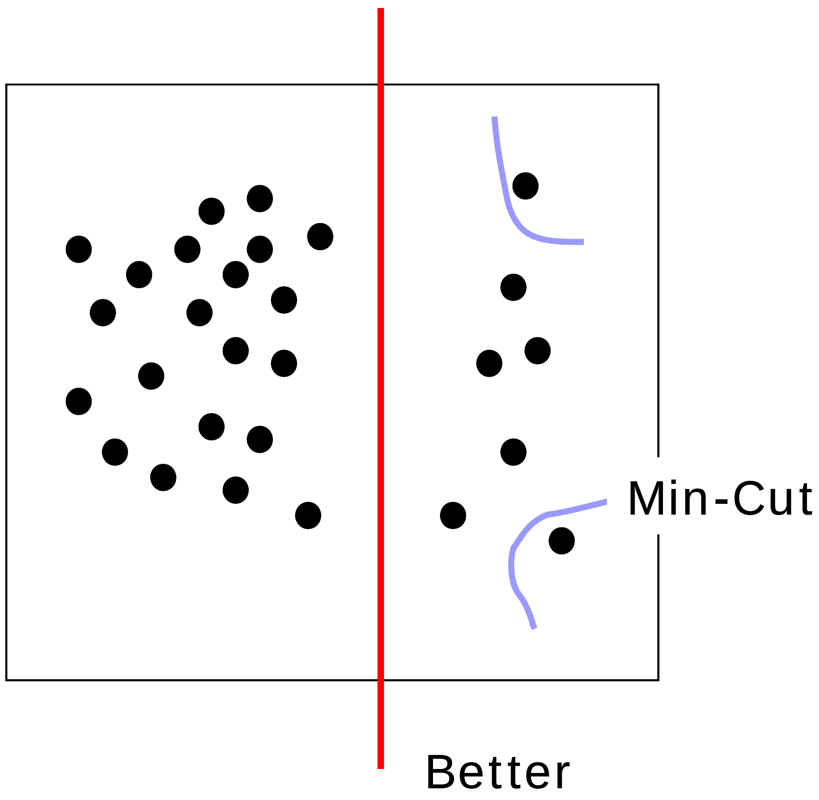
Segmentation: *Method min-cut*:

Find connected components $C_1,..,C_n$ separated by weakest edges (minimum *cut*) and with high *association* (sum of the affinities inside C_i)



2 Image segmentation
2.6 Normalized cuts

Method minimum-cut: Fast and foolish



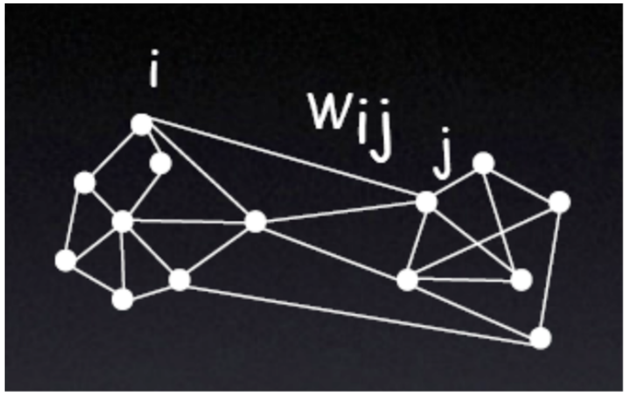
Normalized Cut is NP-Hard!!!!

↓

Spectral Partitioning, introduced in the 1970's by Fiedler, and popularized by Pothen,Simon, & Liu in 1990.

These methods relate graph partitions to the eigenvectors of the Graph-Matrix **A** or its *Laplacian* (**D-A**).

2 Image segmentation
2.6 Normalized cuts (Image Seg)

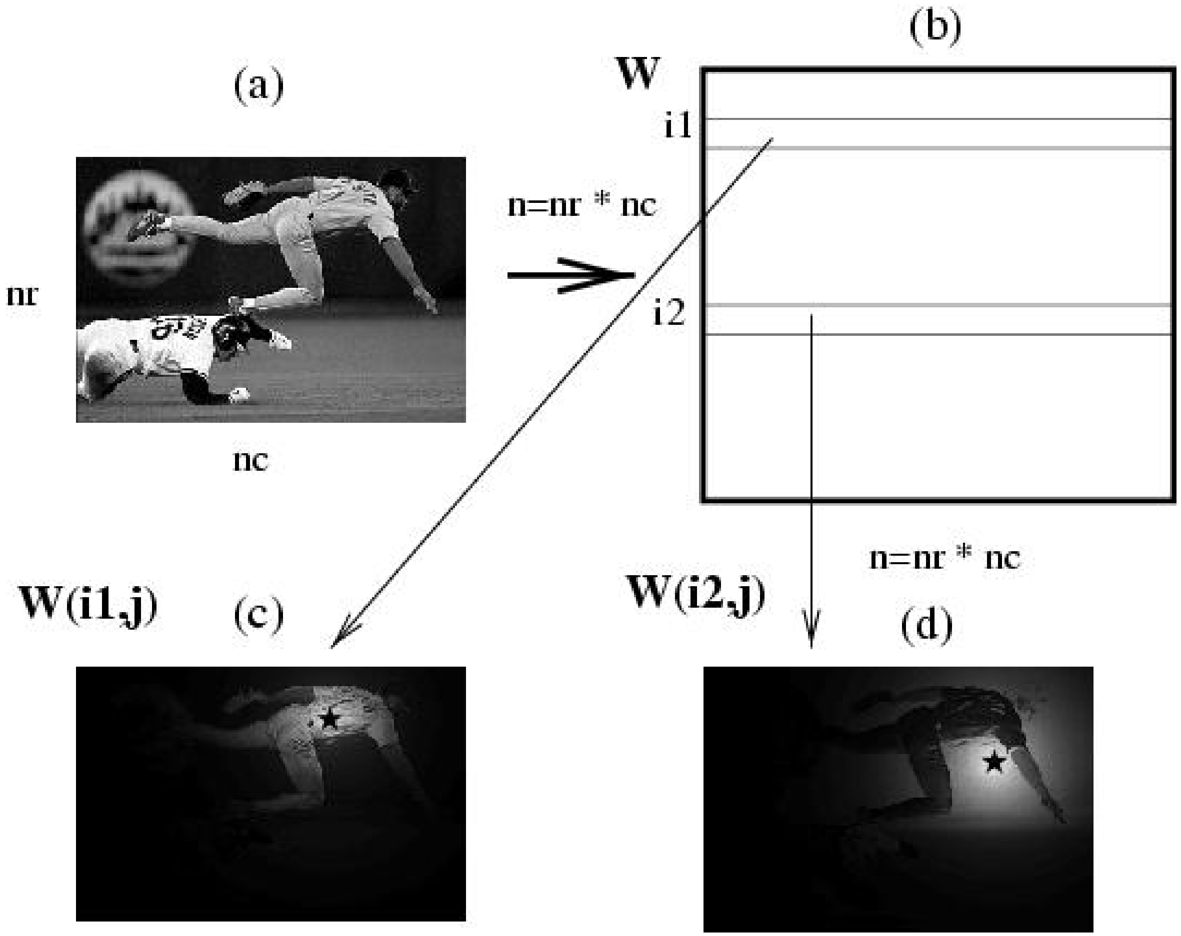


$$G = \{V, E\}$$

V: Graph nodes ⟷ image={pixels}

E: Edge ⟷ Pixel similarity

2 Image segmentation
2.6 Normalized cuts (Image Seg)



2 Image segmentation
2.6 Normalized cuts (Image Seg)

Weight values:

$$\omega(i, j) \begin{cases} \text{Value near 1 is a similarity between the pixels.} \\ \text{A Value near 0 is a dissimilarity between pixels.} \end{cases}$$

Range=[0,1]

Each graph node is a pixel and edge weights are based on features such as spatial proximity, pixel intensity, HSV colour, texture and motion

2 Image segmentation
2.6 Normalized cuts (Image Seg)

Intensity

$$w(i,j) = e^{\frac{-\left\| I_{(i)} - I_{(j)} \right\|_2^2}{\sigma_I^2}}$$

Distance

$$w(i,j) = e^{\frac{-\left\| X_{(i)} - X_{(j)} \right\|_2^2}{\sigma_X^2}}$$

Texture

$$w(i,j) = e^{\frac{-\left\| c_{(i)} - c_{(j)} \right\|_2^2}{\sigma_c^2}}$$

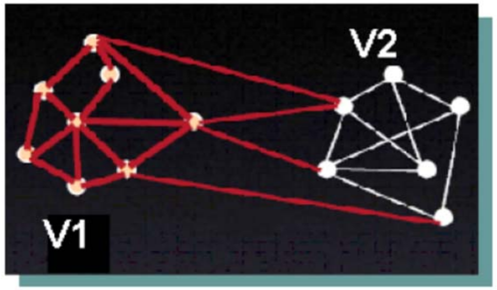
2 Image segmentation
2.6 Normalized cuts (Image Seg)

- Normalized cuts penalise unbalanced segments by normalizing the cut cost with the size of segments

$$Ncut(V_1, V_2) = \frac{cut(V_1,V_2)}{assoc(V_1,V)} + \frac{cut(V_1,V_2)}{assoc(V_2,V)}$$

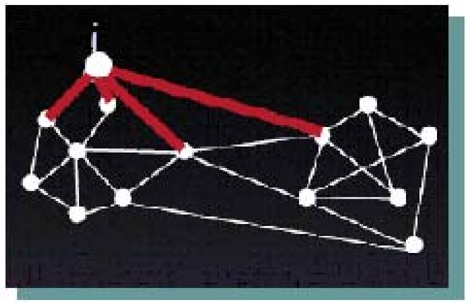
- Size of a segment is based on its association, which is the sum of the edge weights from every node in V1 to every node in V2 that touches V1

$$assoc(V_r, V_t) = \sum_{u \in V_r, v \in V_t} w(u, v)$$



2 Image segmentation
2.6 Normalized cuts (Image Seg)

- Minimizing Ncut simultaneously maximizes the disassociation between V1 and V2 and the similarity between nodes within V1 and V2
- Can minimise Ncut efficiently by expressing it as a generalised eigenvalue problem:



$$(D-W)y = \lambda Dy$$

- D is a diagonal matrix containing the degree of each node $d(i) = \sum_j w(i,j)$
- W is the affinity matrix of the edge weights
- y and λ are the eigenvectors and eigenvalues which can be used to determine the location of the cut

2 Image segmentation
2.6 Normalized cuts (Image Seg)

- **Recursive 2-Way Normalised Cut Grouping Algorithm:**

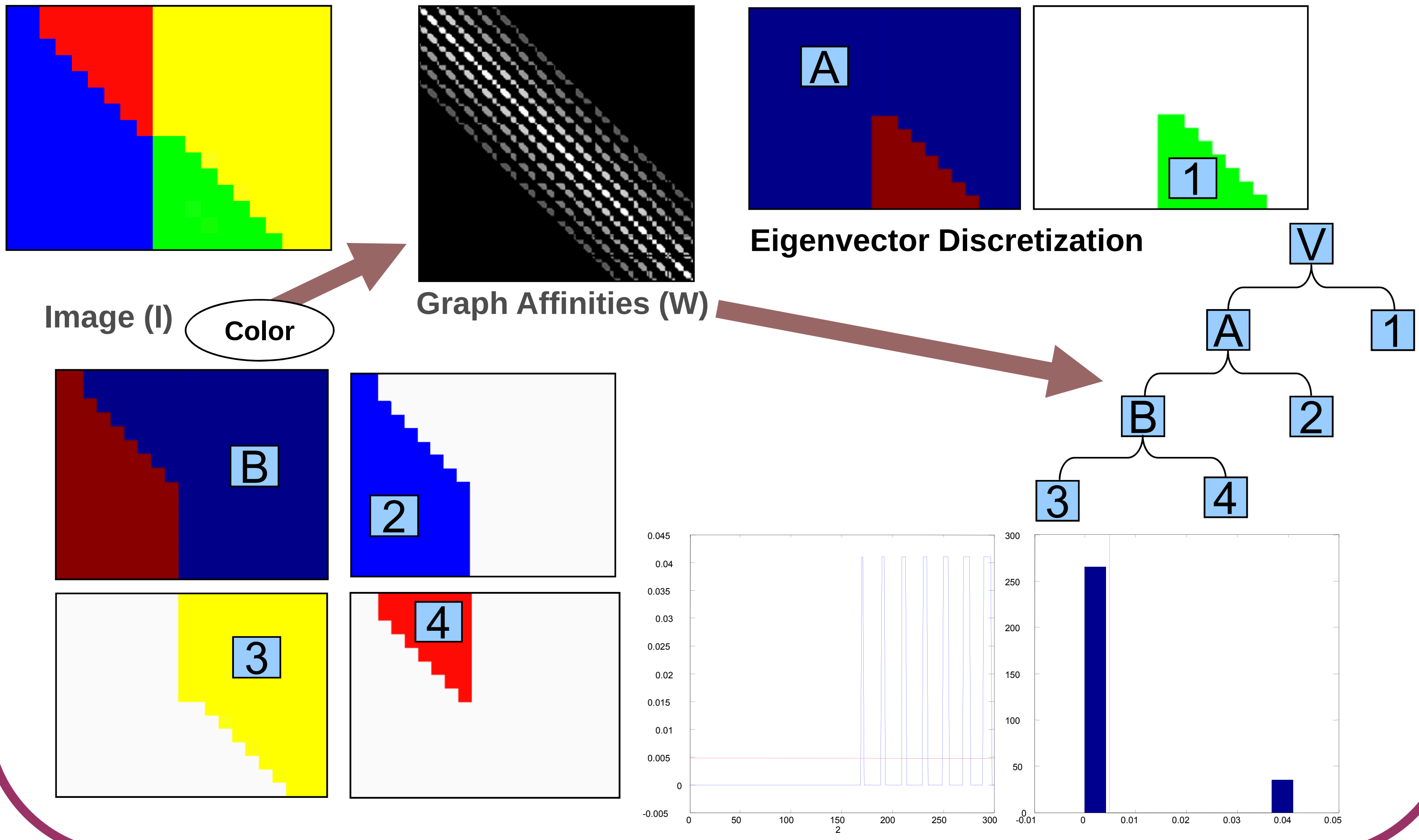
1. Produce a fully connected graph G = (V,E) of the nodes and compute the corresponding weights w(p,q) for each edge.

2. Solve the generalised eigenvalue problem $(D-W)y = \lambda Dy$ to obtain the eigenvectors (y) and eigenvalues (λ)

3. Use the eigenvector corresponding to the second smallest eigenvalue to bi-partition the graph.

4. Recursively partition the two new segments if necessary by checking the stability of the cut

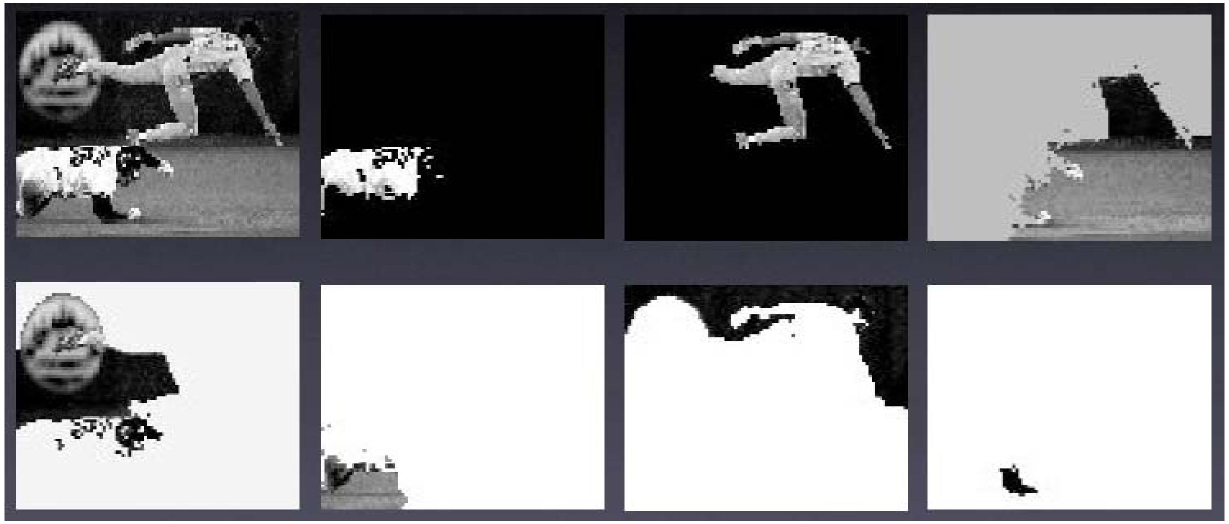
2 Image segmentation
2.6 Normalized cuts (Image Seg)



https://www.cis.upenn.edu/~jshi/software/

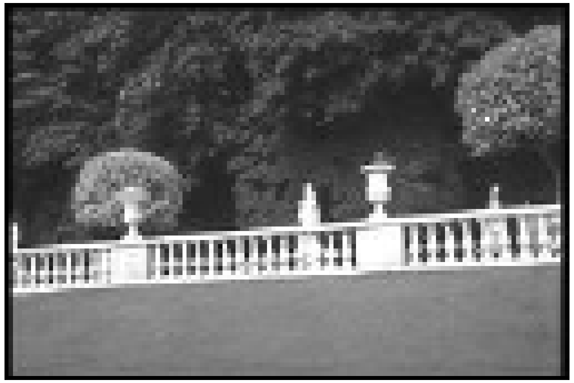
2 Image segmentation
2.6 Normalized cuts (Image Seg)

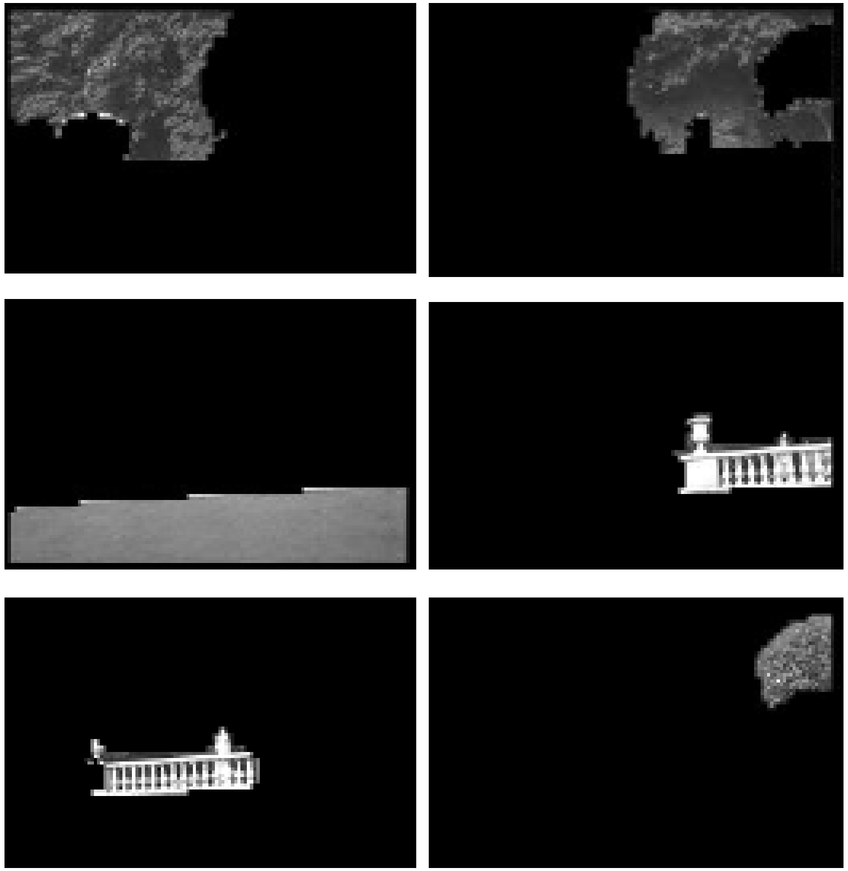
Example 1

2 Image segmentation
2.6 Normalized cuts (Image Seg)

Example 2





Conclusions

- Normalized cut presents a new optimality criterion for partitioning a graph into clusters.
- The discrete problem corresponding to Min Ncut is NP-Complete.
- We solve an approximate version of the MinNcut problem by converting it into a generalized eigenvector problem.

2 Image segmentation
2.6 Normalized cuts (Image Seg)

References

-Graph based image segmentation:

Shi &Malik. Normalized cuts and image segmentation. PAMI 22(8) 2000.

https://www.cis.upenn.edu/~jshi/software/

Depuis & Vasseur. Image segmentation by cue selection and integration. IVC 24 2006.

2 Image segmentation

1. Definitions, representation and evaluation results
2. Region based methods
3. Clustering based methods
4. Other methods
5. Actual methods

2.6 Normalized Cuts

2.7 Mean Shift

Image Segmentation using Mean Shift

Prepared by:
Wajahat Kazmi(u1066662)
Gaurav Sisodia(u1066668)

Mean Shift Theory

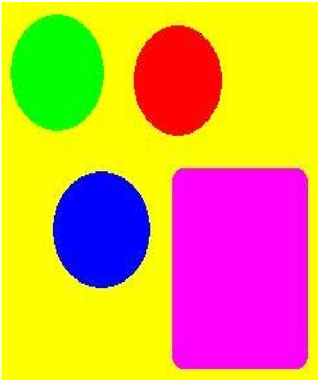
& its application in Computer Vision

Adhiguna Mahendra
Arunkumar Pandian

2 Image segmentation
2.7 Mean Shift

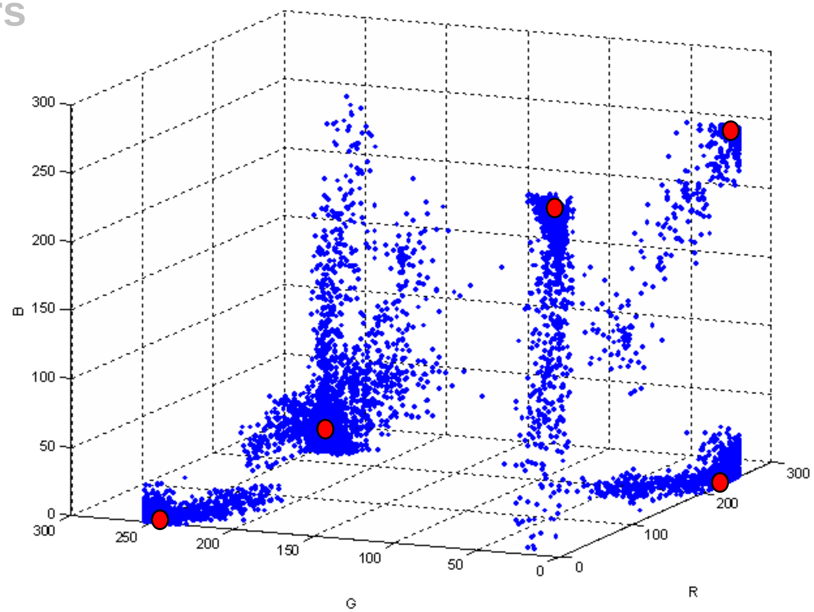
Input Image → Feature Space (N dimensional)

N feature vectors



3 FVs

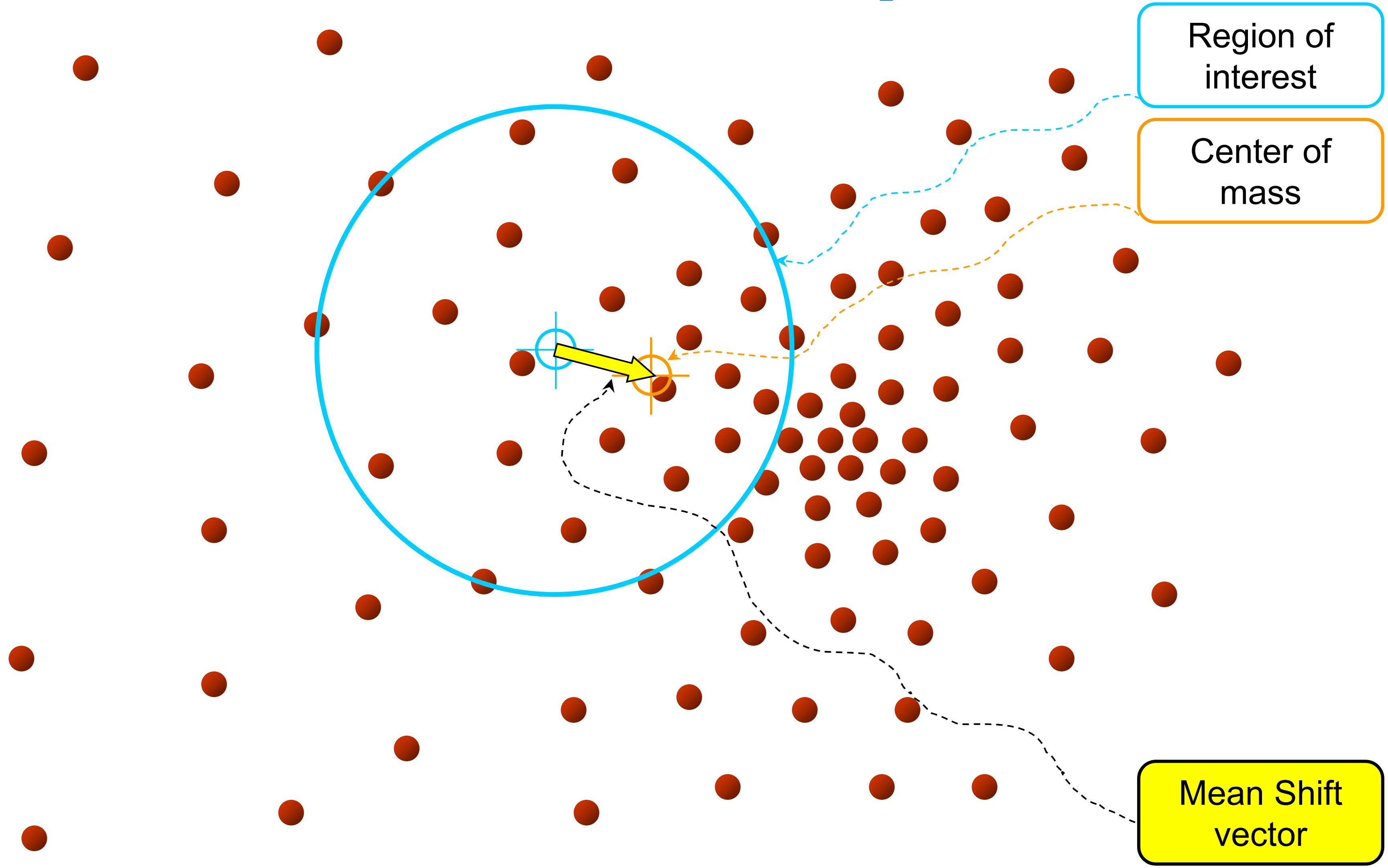
RGB



Significant features → High density regions (Clusters)

❖ Characterising arbitrarily shaped clusters: Non-parametric method

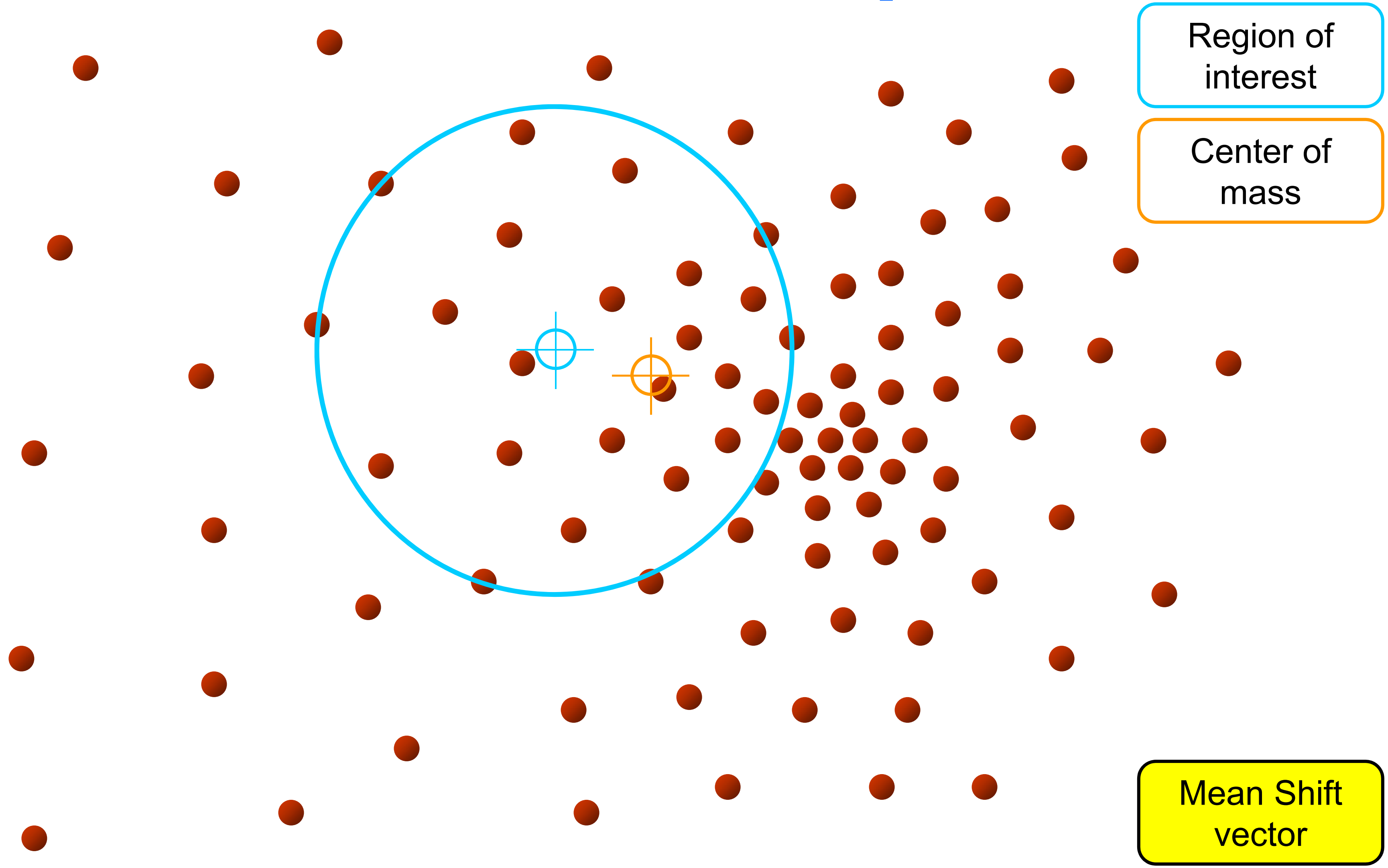
Intuitive Description



Objective : Find the densest region

Distribution of identical billiard balls

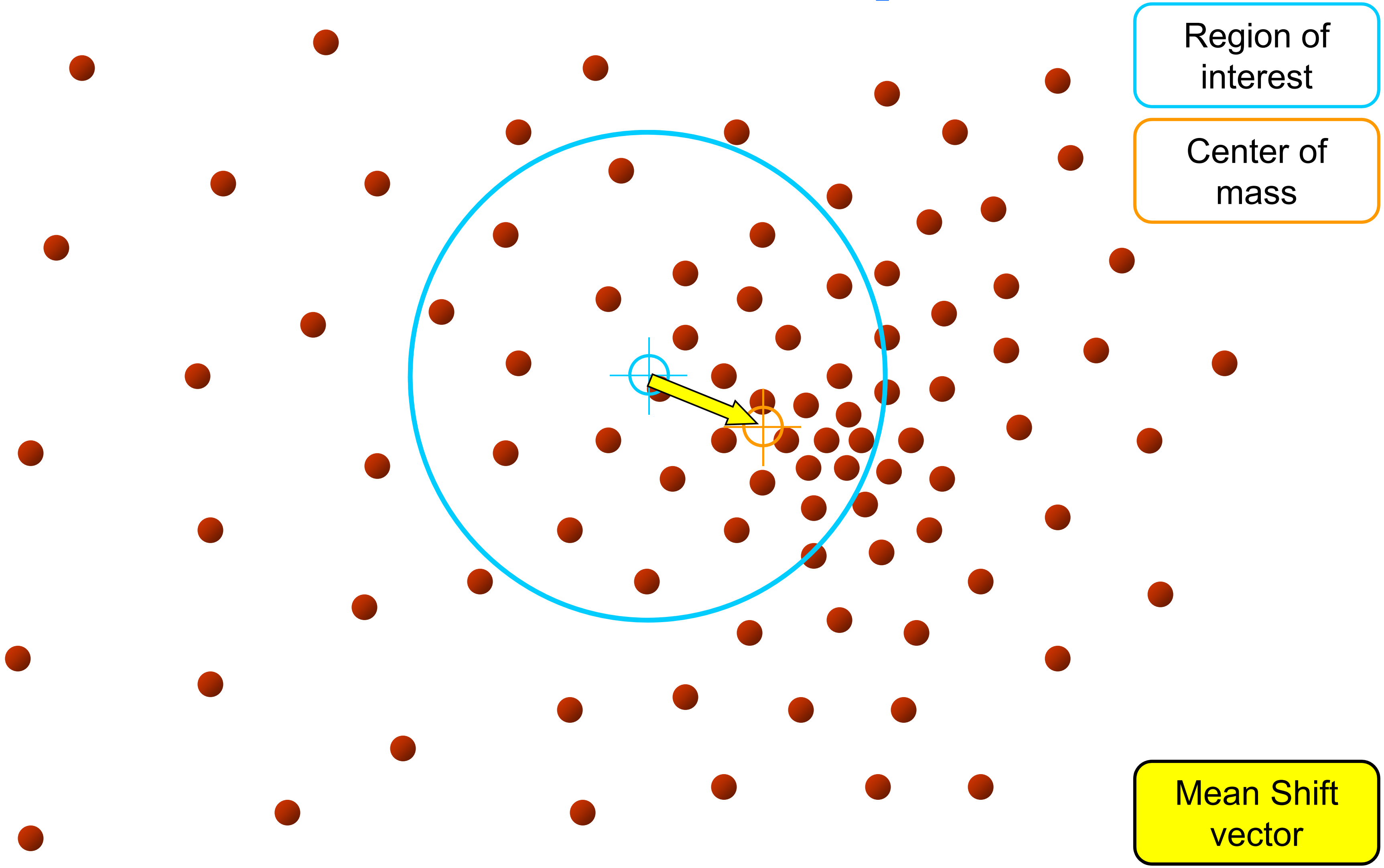
Intuitive Description



Objective : Find the densest region

Distribution of identical billiard balls

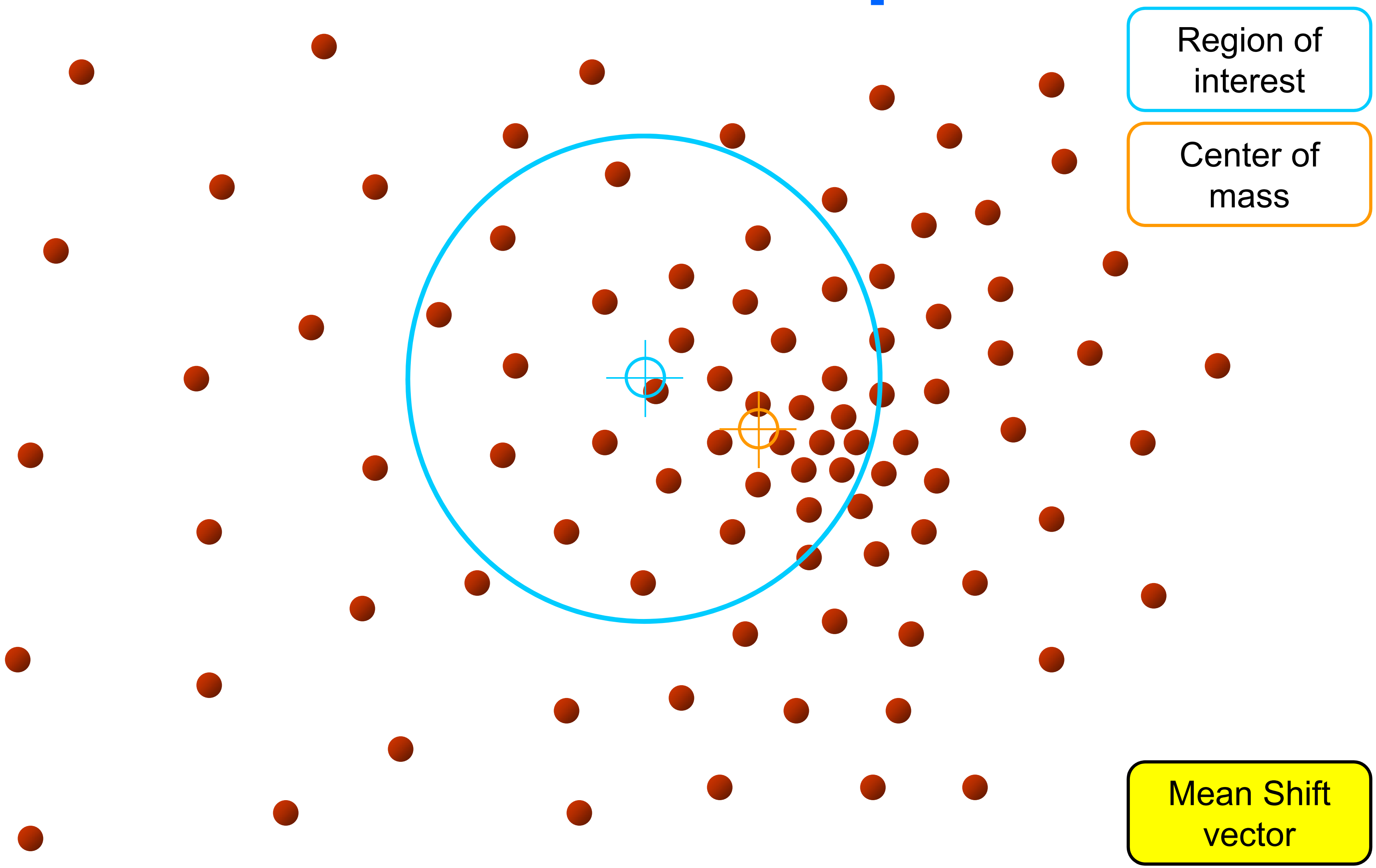
Intuitive Description



Objective : Find the densest region

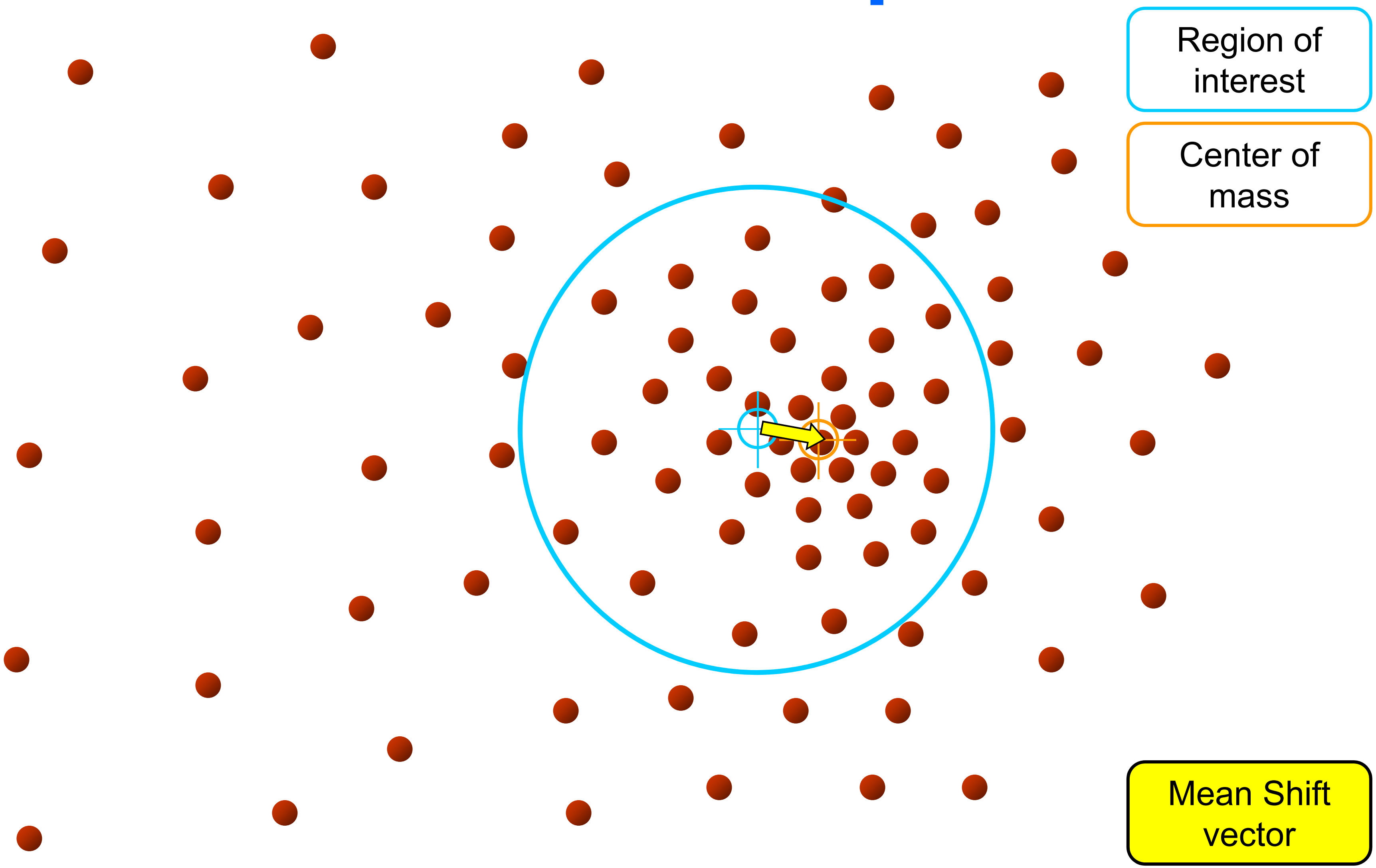
Distribution of identical billiard balls

Intuitive Description



Objective : Find the densest region
Distribution of identical billiard balls

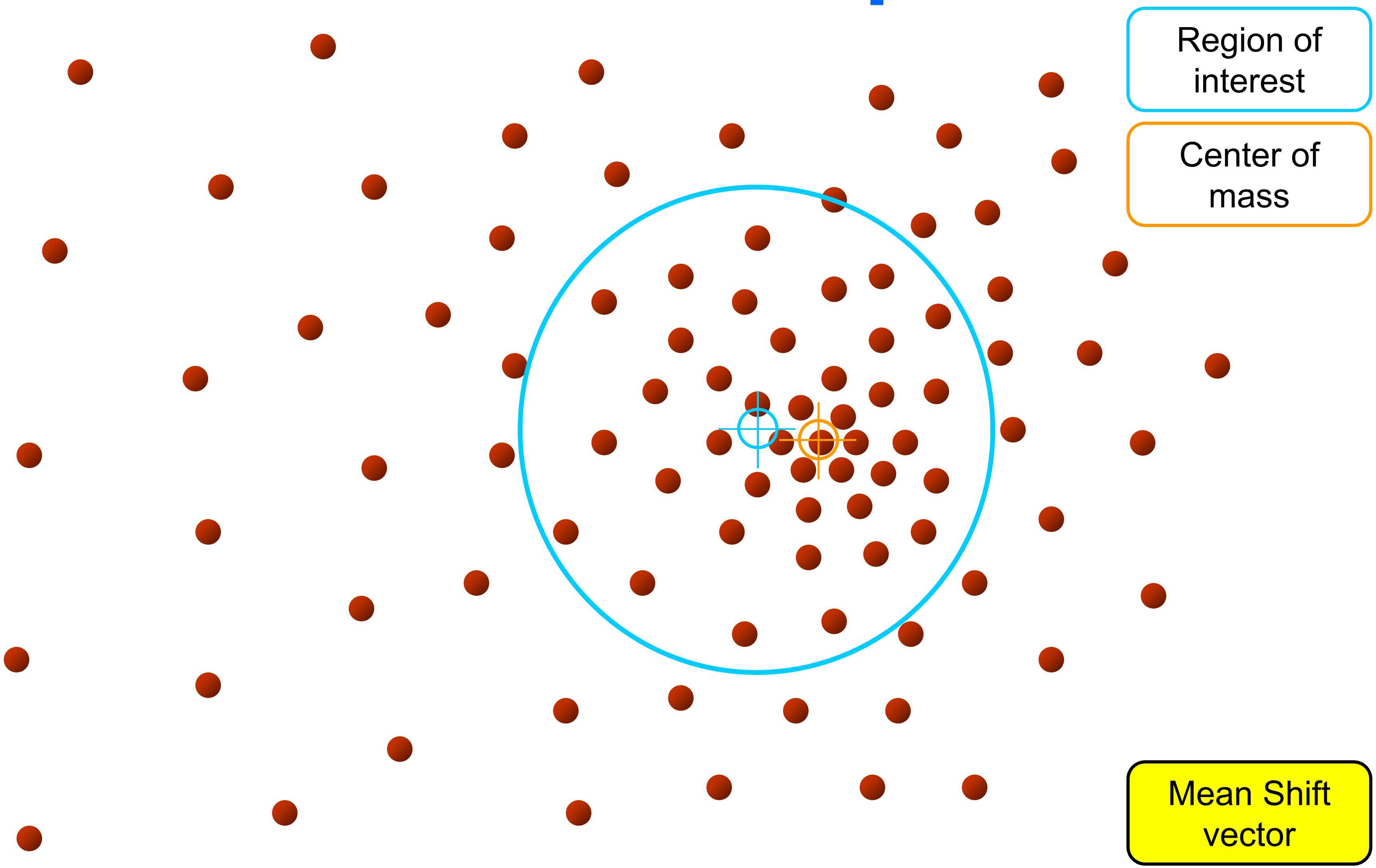
Intuitive Description



Objective : Find the densest region

Distribution of identical billiard balls

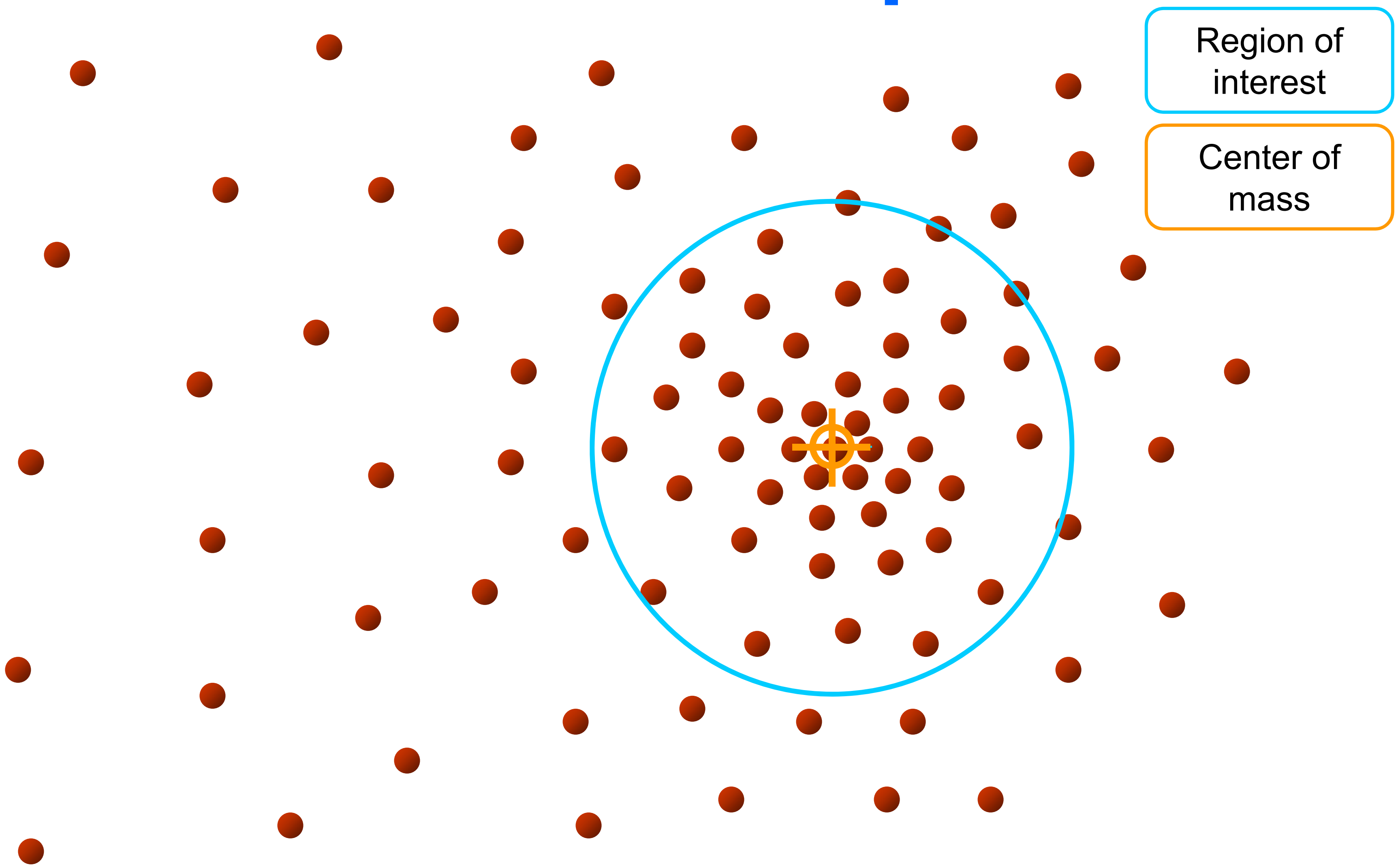
Intuitive Description



Objective : Find the densest region

Distribution of identical billiard balls

Intuitive Description

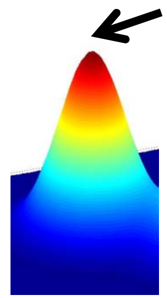


Objective : Find the densest region

Distribution of identical billiard balls

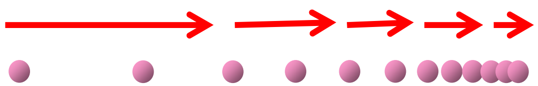
Mean Shift in detail

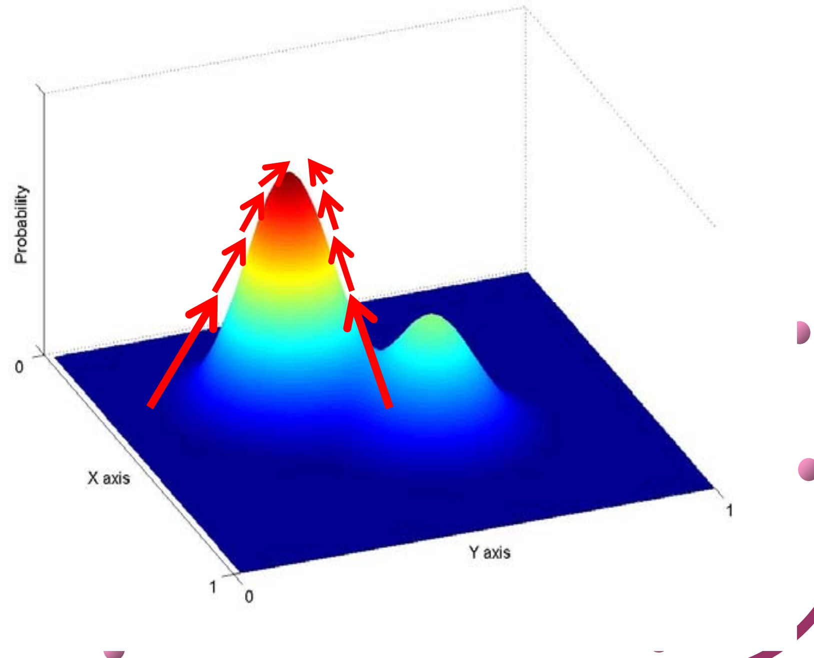
- **Objective**: To locate the **modes (peaks)** of empirical probability density function (feature space)
- Mean shift → normalised density gradient estimation



$$m_{h,G} = \frac{1}{2} h^2 c \frac{\nabla f_{h,K}(x)}{f_{h,G}(x)}$$

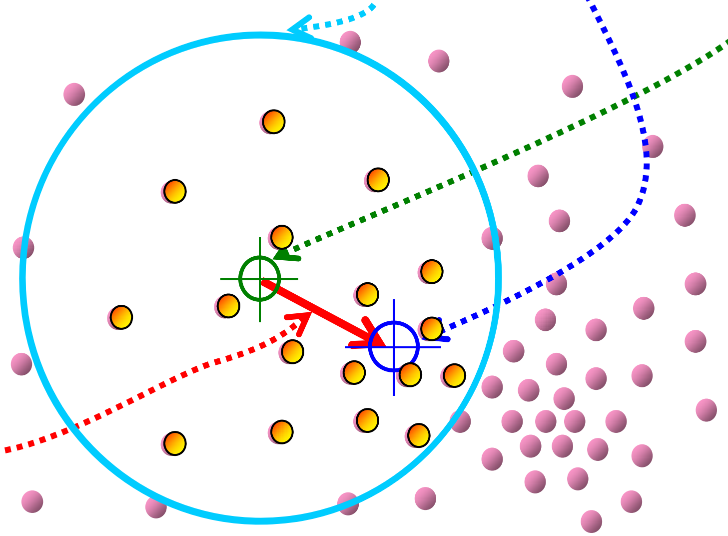
Adaptive Gradient Ascent





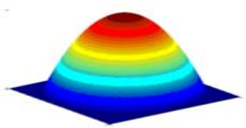
2.7 Mean Shift in detail

$$m_{h,G}(x) = \boxed{\frac{\sum_{i=1}^{n} x_i G\left(\left\|\frac{x - x_i}{h}\right\|\right)}{\sum_{i=1}^{n} \boxed{G}\left(\left\|\frac{x - x_i}{h}\right\|\right)}} - \boxed{x}$$

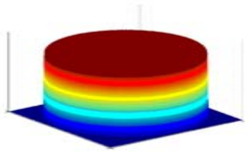


Kernels

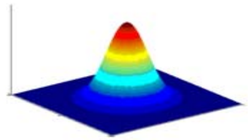
Epanechnikov



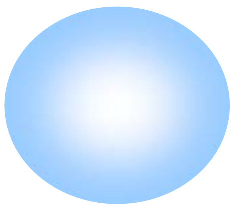
Uniform



Normal



Bandwidth matrix H



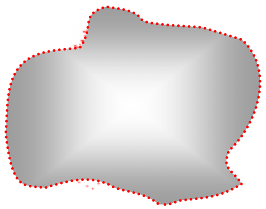
$$\begin{bmatrix} h & 0 \\ 0 & h \end{bmatrix}$$

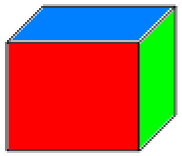
$$\begin{bmatrix} h/4 & 0 \\ 0 & h/4 \end{bmatrix}$$

Comparison — Mean Shift Vs ?

Mean Shift		K-Means
Non-parametric	⟺	Parametric (Parameter: No of clusters - **K**)

Mean Shift		Thresholding
Can accommodate **arbitrary cluster shapes** - *suited for real distributions*	⟺	Restricts the shape of a feature segment: CUBE [T_R, T_G, T_B] Parametric: Value of threshold



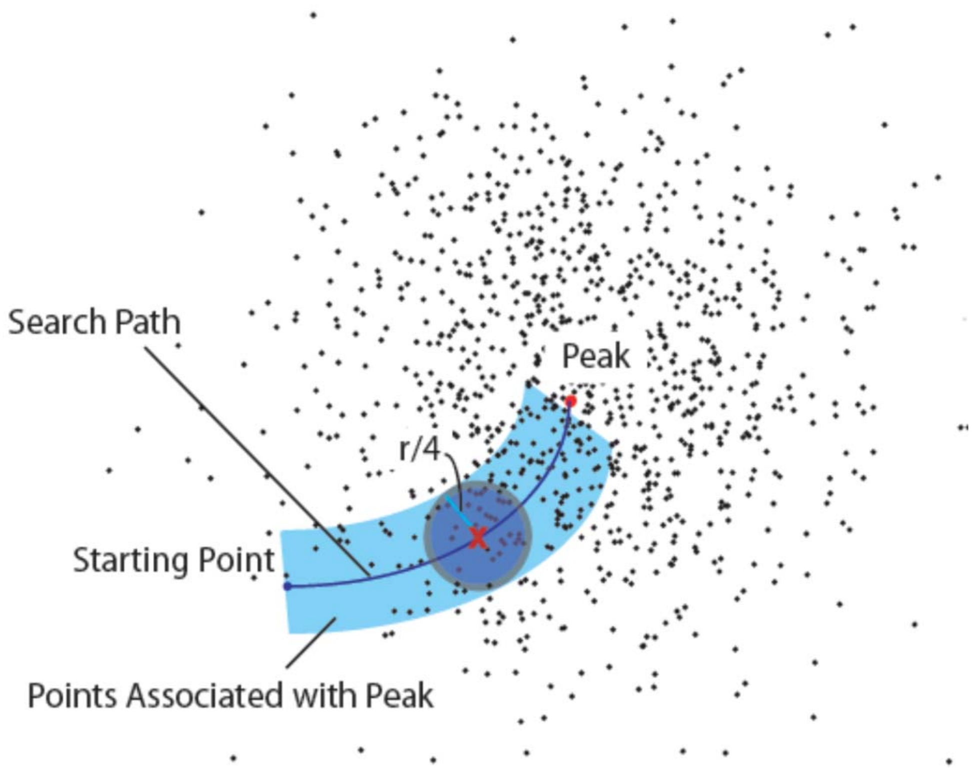


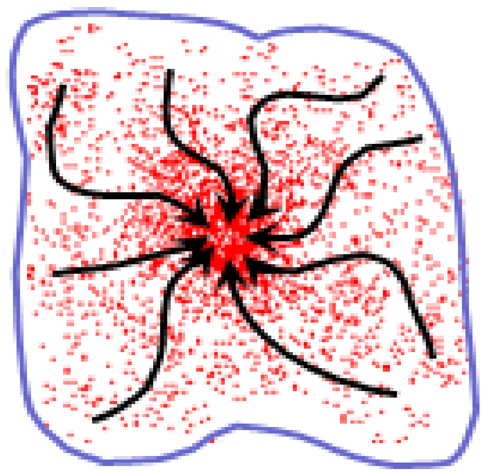
Algorithm for Mode Detection

Mean Shift Algorithm

- Choose the radius r of the search window.
- Choose the initial location of the window.
- Compute the mean shift vector and translate the search window by that amount.
- Repeat till convergence.

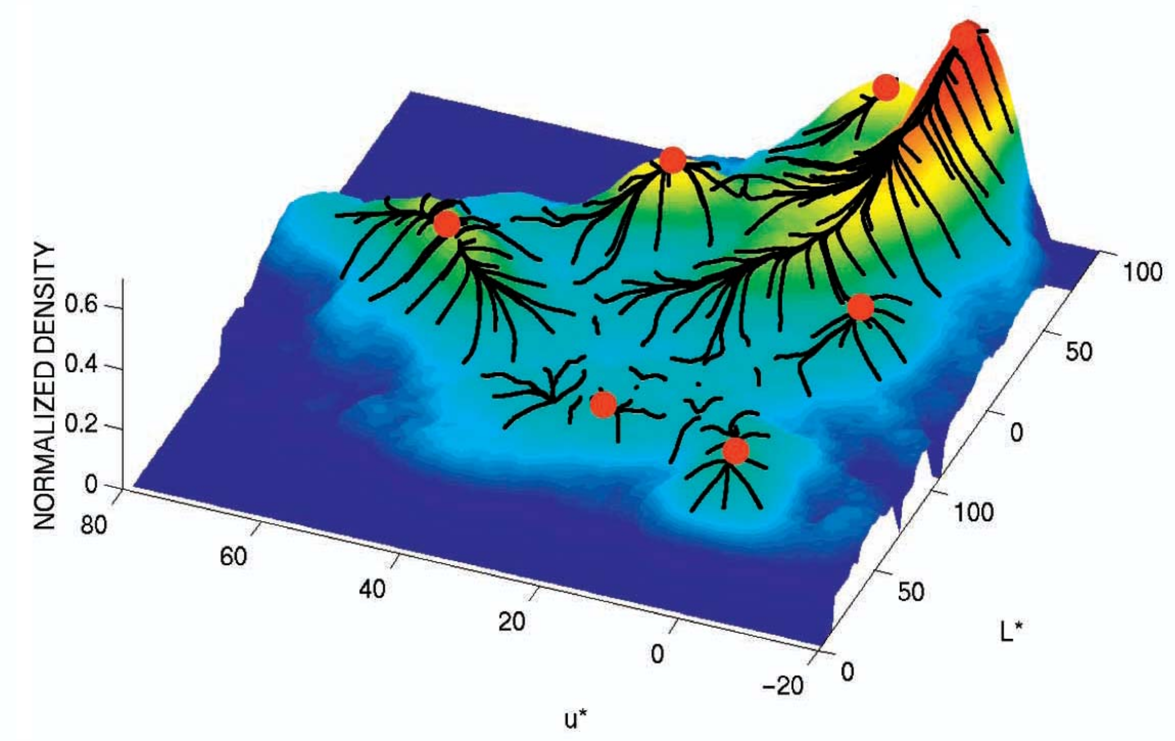
Peak Detection/Basin of Attraction





1. Points along the search path are associated with the converged peak.
2. Basin of Attraction: Region for which all trajectories lead to the same mode

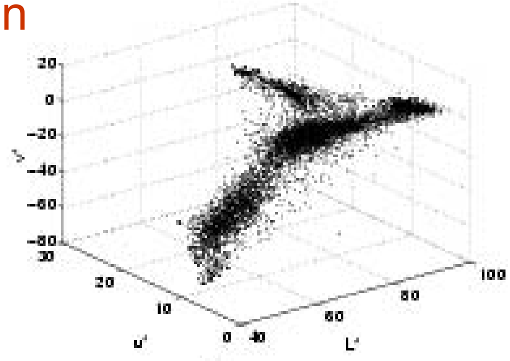
Peak Detection/Basin of Attraction



Clustering

Real Example

Feature space:
L*u*v representation



(a)

ⁱⁿitial window
enters

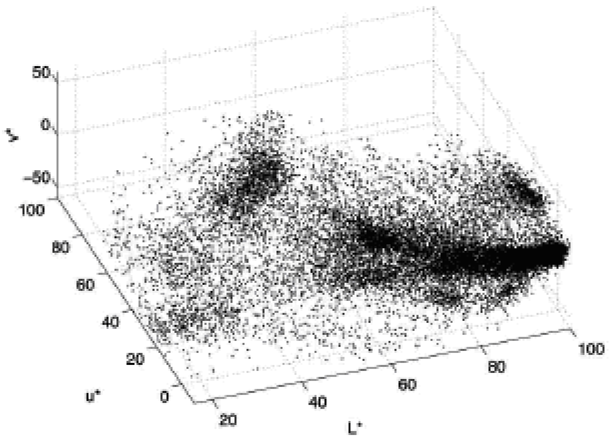
M

pruning

Segmentation: Step 1

- Map the image domain into the feature space (d-dimensional input consisting of i,j (pixel positions) and RGB/LUV or i,j (pixel positions) and Gr in the joint spatial-range domain).

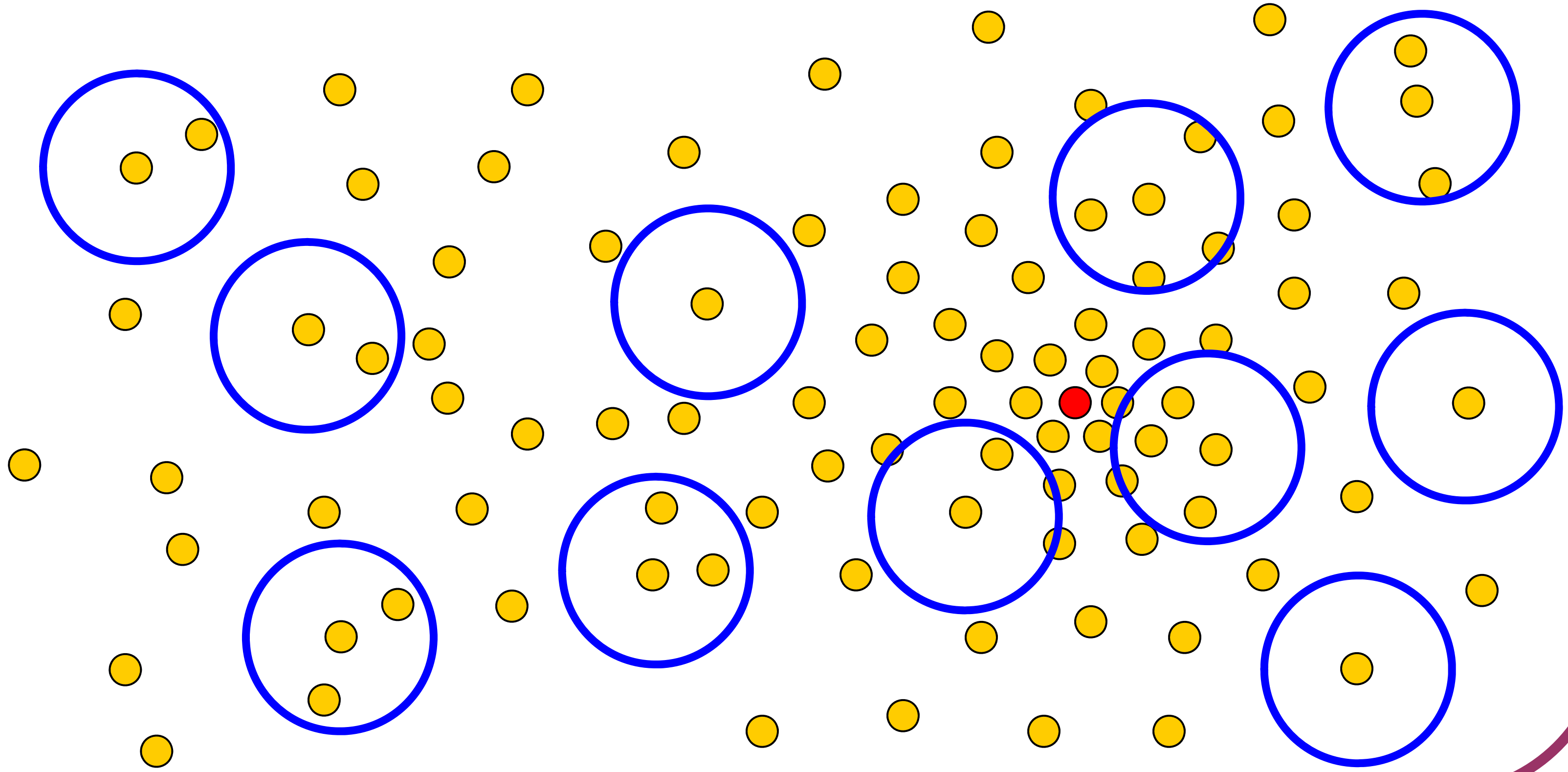
Color Image (400x276)



Corresponding LUV Feature Space

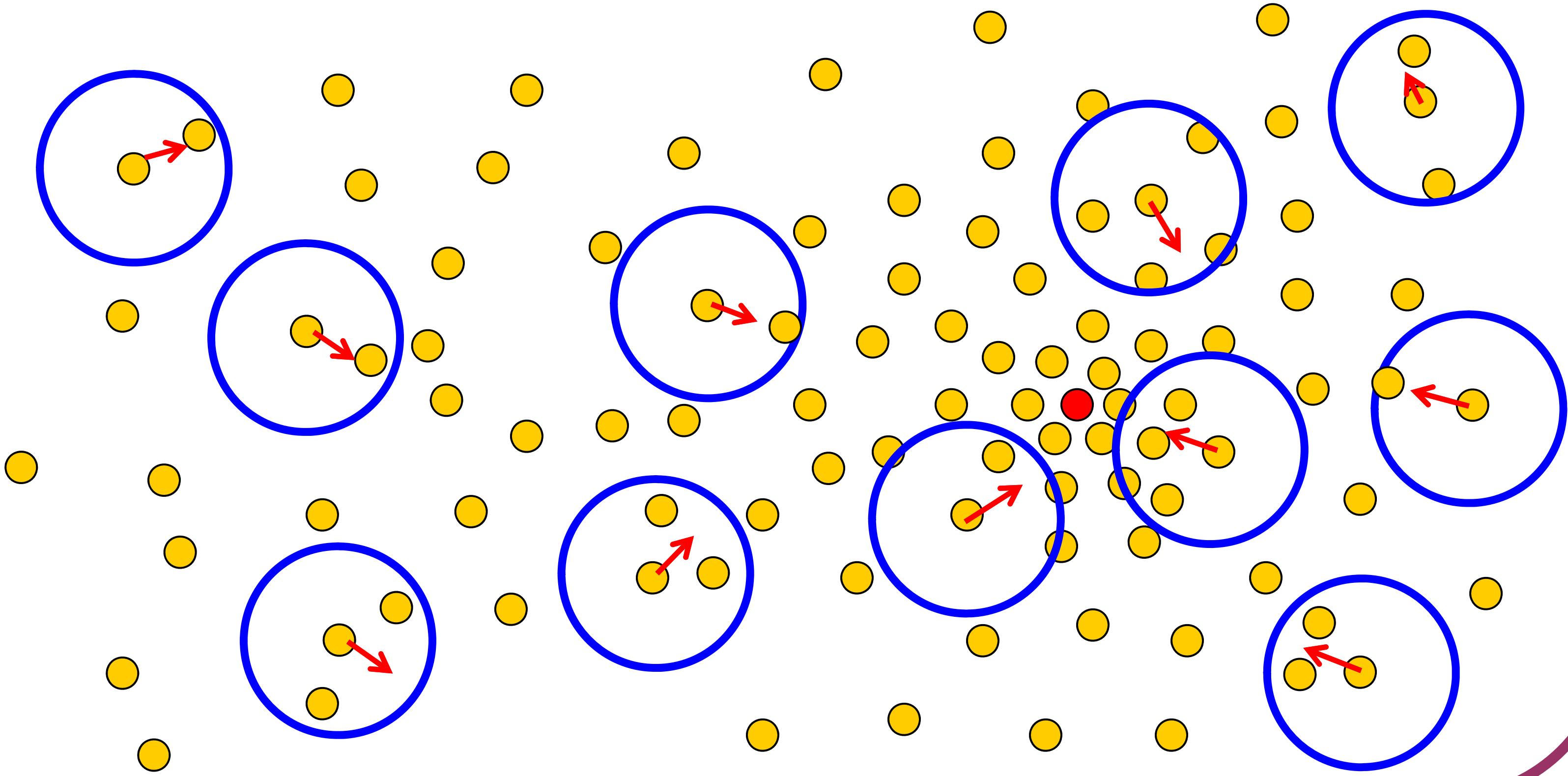
Step 2

- Define an adequate number of search windows at random locations in the space.



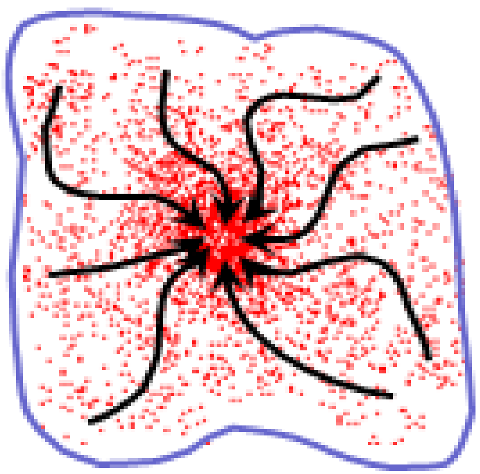
Step 3

- Find the high density region centers by applying the mean shift algorithm to each window.



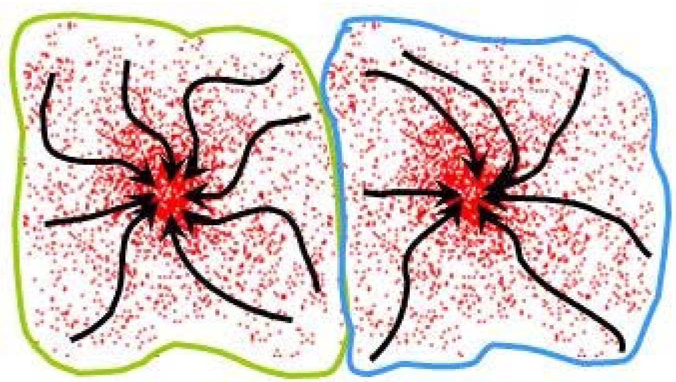
Step 4

- Associate points along the search path to the peak zi



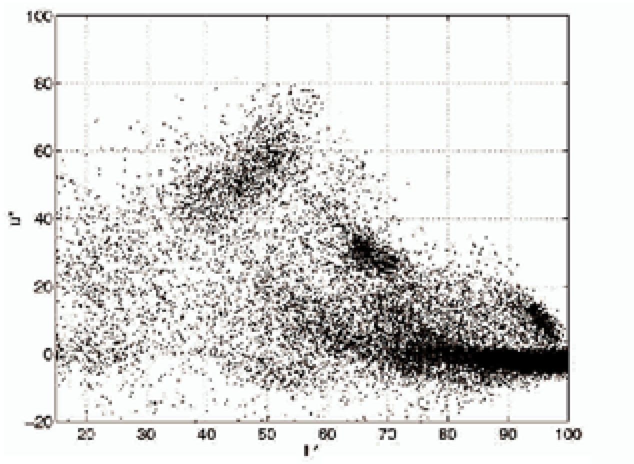
Step 5

- Delineate the clusters by grouping together *all zi* which are closer than *window size* i.e. concatenate the basins of attraction of the corresponding convergence points.

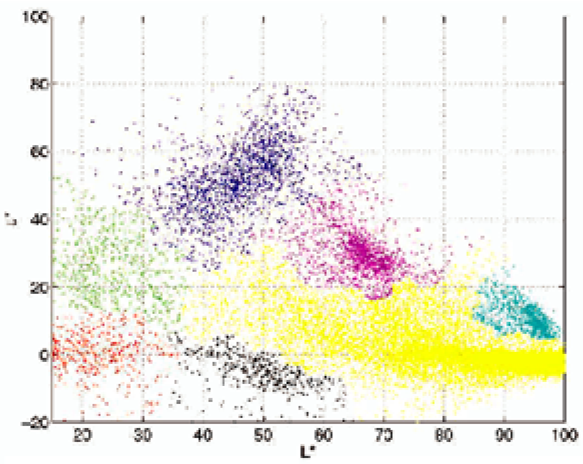


Step 6

- For each *i=1,...,n,* assign *Li = {p | zi Є Cluster i}.*
- Optional: Eliminate spatial regions containing less than *M* pixels.
- The cluster delineation step can be refined according to a priori information.



2D (L*u) space representation



Final clusters

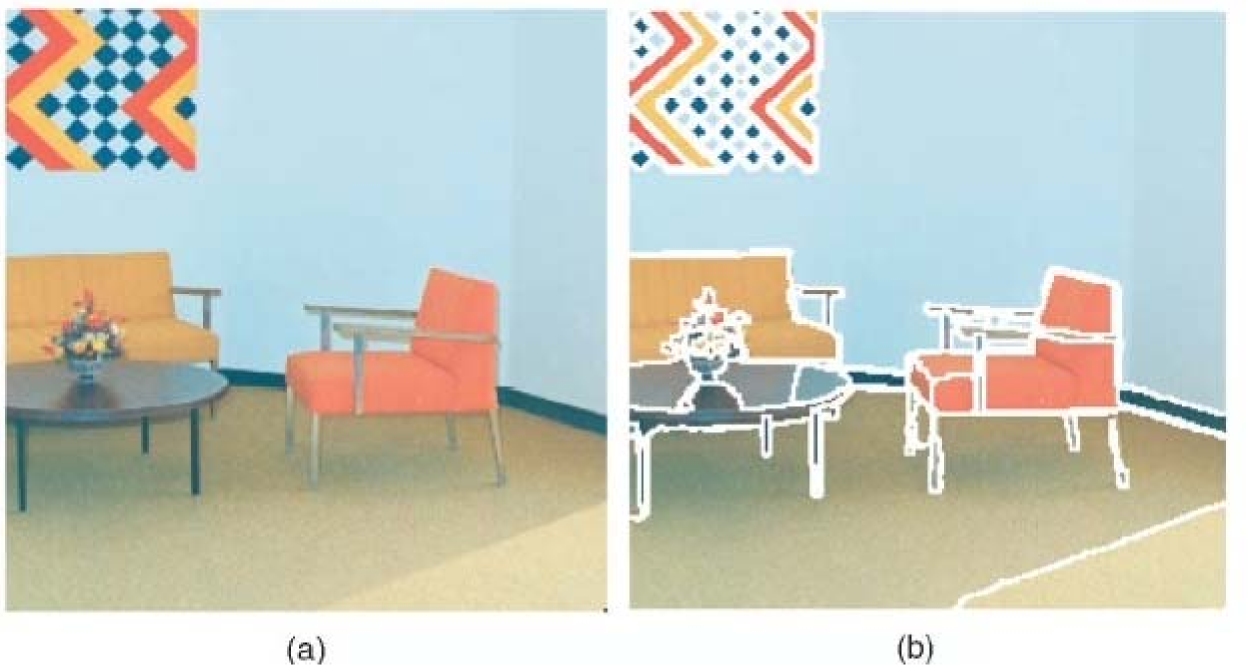
2.7 Segmentation result

(a) (b)

(a) Original. (b) Segmented $(h_s, h_r, M) = (8, 7, 20)$

Image : Yaron Ukrainitz and Baron Sarel, Weizmann Institute Israel

2.7 Segmentation result



Room image. (a) Original. (b) Region boundaries delineated with $(h_s, h_r, M) = (8, 5, 20)$

Image : Yaron Ukrainitz and Baron Sarel, Weizmann Institute Israel

2.7 Segmentation result

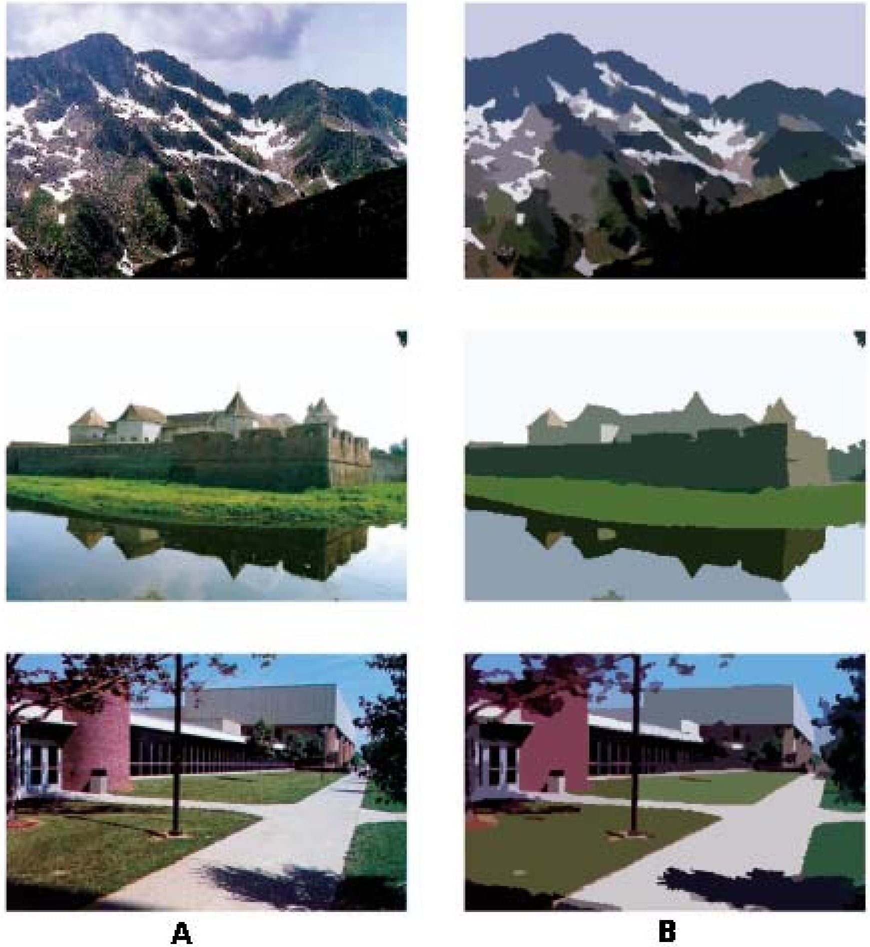


Image : Dorin Comaniciu, Rutgers University

References

- [1] Mean Shift: A Robust Approach Toward Feature Space Analysis, Dorin Comaniciu and Peter Meer. *IEEE Transactions on Pattern analysis and machine intelligence.* Vol 24, No.5, May 2002.

- [4] Sze Hon Yan, Somnuk Phon-Amnuaisuk. *A Case Study Of Mean Shift In Image Segmentation.*

- http://www.wisdom.weizmann.ac.il/~vision/courses/2004_2/files/mean_shift/mean_shift.ppt.

2 Image segmentation

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