MLRF Lecture 01

J. Chazalon, LRE/EPITA, 2023

Global Image Descriptors

Lecture 01 part 05

The need for image descriptors

Issues with methods based on pixel comparison

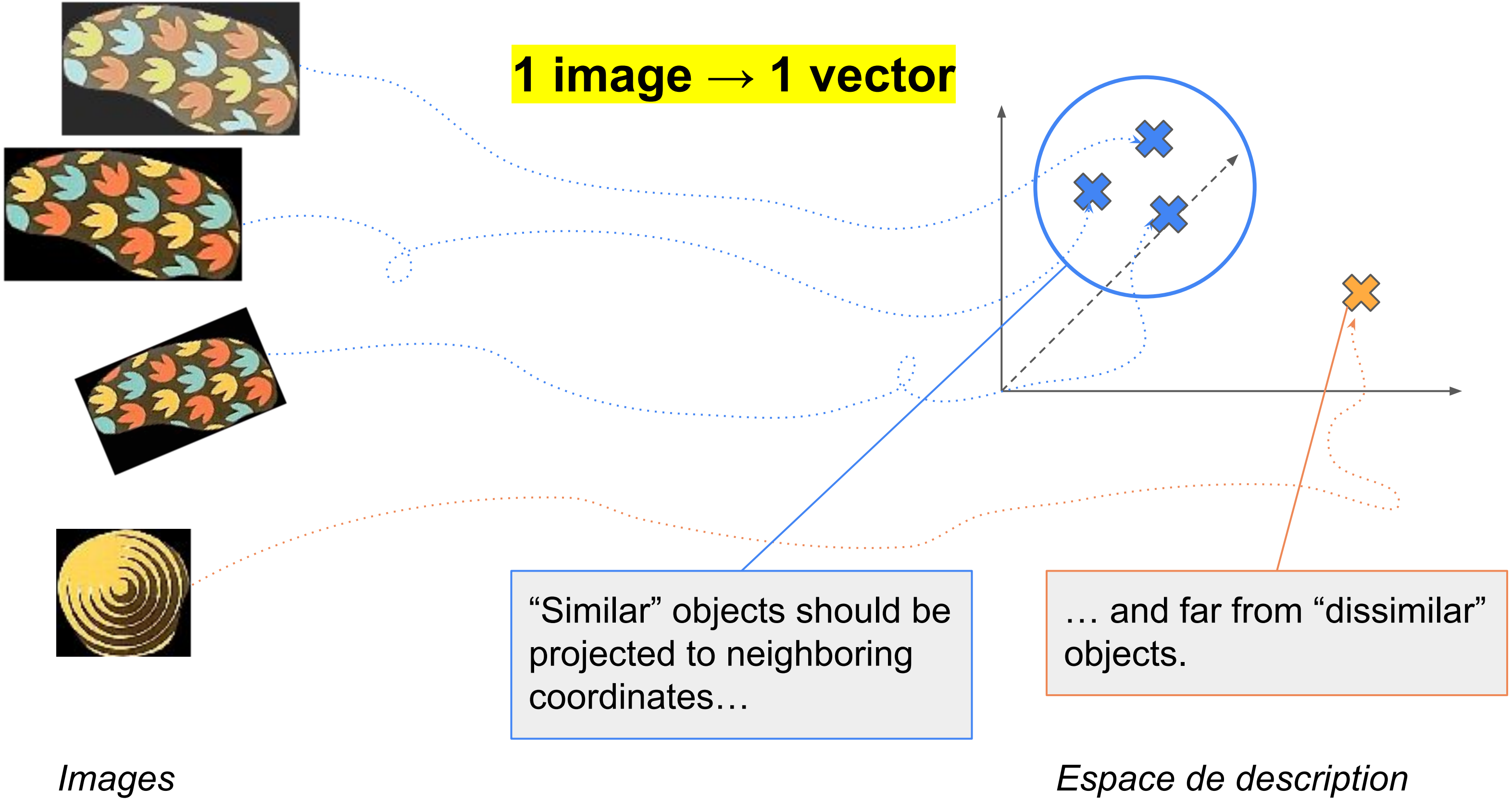
What is important? What do they consider? **Raw pixels!**
⇒ We want to be able to make use of **domain knowledge**!
Like sensitivity to shape, or dominant color information.

They are terribly **slow** and works **only for small images.**
⇒ We want to **summarize an image** to a much smaller vector.

They are **sensible to rotation, scaling**, and many other perturbations.
⇒ We want to adjust sensitivity/invariance to perturbations.
Do we tolerate translation? Rotation? Intensity shift?

How can we compare different pairs of images? **Metric issues.**
⇒ We want to be able to achieve **more than 1 vs all comparisons.**

Global descriptors in 1 picture



Two approaches

Lecture 4

Global image descriptors

- Compute **statistics about the content** of the image
- Produce a **single global vector**

Very attractive because they are very fast to compute and match, but… (see end of section)

Bag of Features techniques

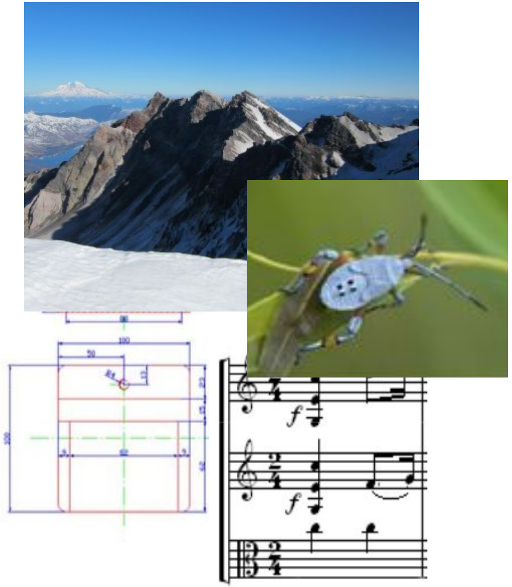
- **Select regions** of interest in the image (may be a variable quantity)
- **Compute descriptors** for each region
- **Index each part** separately (like a text search engine which indexes words)

It is always possible to build a single descriptor from local descriptors!

This technique is the one used in modern image search engines.

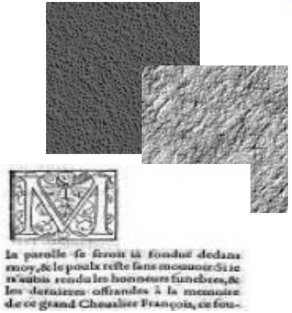
Image descriptors: Overview

Different sizes and contents ⇒ Different kind of descriptors



Large images, many parts

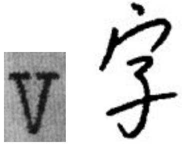
Complex small images



Textured areas

Logos

Words



Isolated symbols and letters

Local image patches, lines, etc.

≈ 500×500 px and more ≈ 20×20 px and less

Image descriptors: Overview

Different sizes and contents ⇒ Different kind of descriptors

Different problems ⇒ Different choices

- Computation / memory constraints
- Which perturbations to we have to tolerate?
  rotation, translation…
- What is the expected output?
  classification, detection, ranking, segmentation…

Many, many approaches ⇒ Impossible to list them all

- Examples of several categories
- Focus on very useful or instructive ones

Color Histograms

Swain, Ballard, “Color indexing”, IJCV’91

Color histograms – a very simple global descriptor (of pixels statistics)

High invariance to many transformation

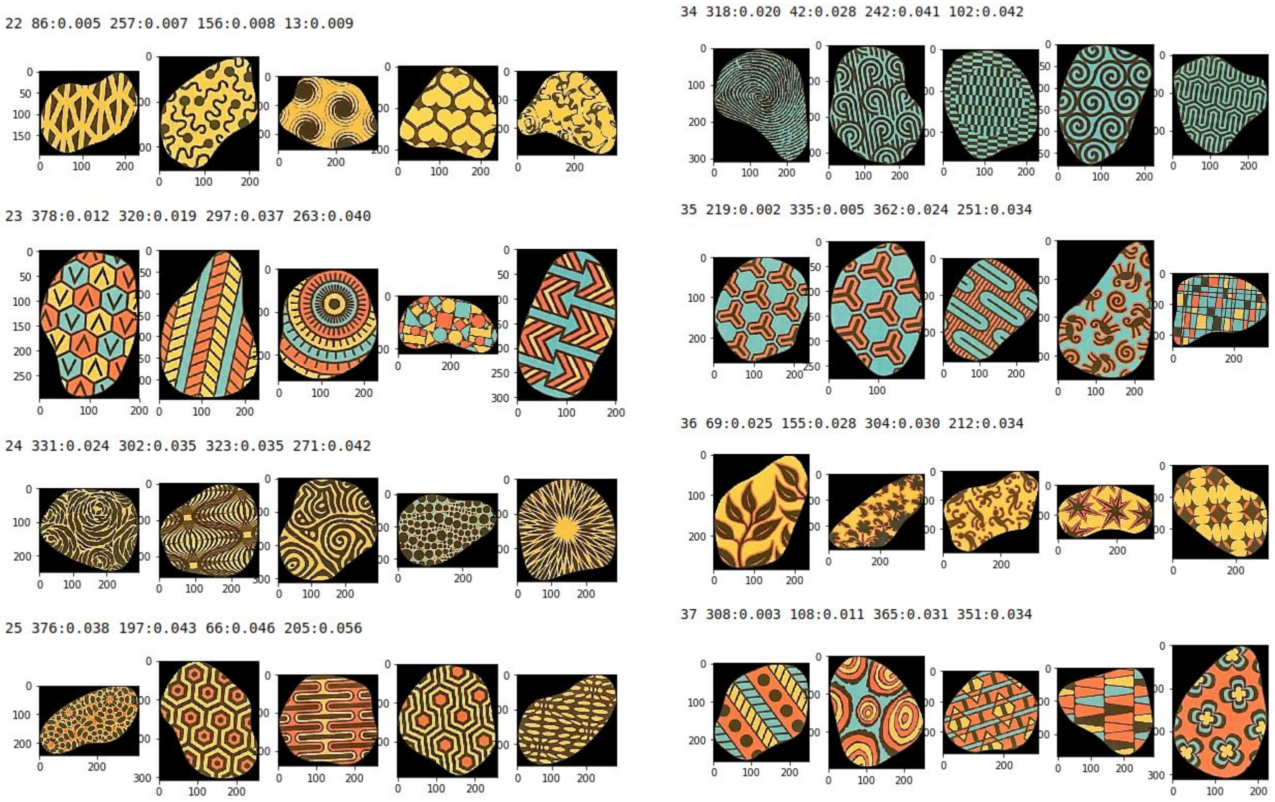
rotation, scaling thanks to normalization, perspective…

But limited discriminative power

Easy to implement

1. Reduce the colors (opt. when performing backprojection)
2. Compute a reduced color histogram on each image
3. Use a distribution distance to compare the descriptors

Color histograms: Some results on *Twin it!*



Timing comparison (1 CPU)

Template matching
Match each pair of image:
3 hours

Color Histogram
Color reduction:
3 seconds

Compute color histogram for all bubbles:
30 seconds

Compute distance between each pair of descriptors:
2 seconds

Color histograms: Step by step

1: Color reduction

1. Use K-Means or any other clustering technique to find *N* useful colors.
2. Project each pixel value on the value of the closest cluster center.

Swain & Ballard 1991

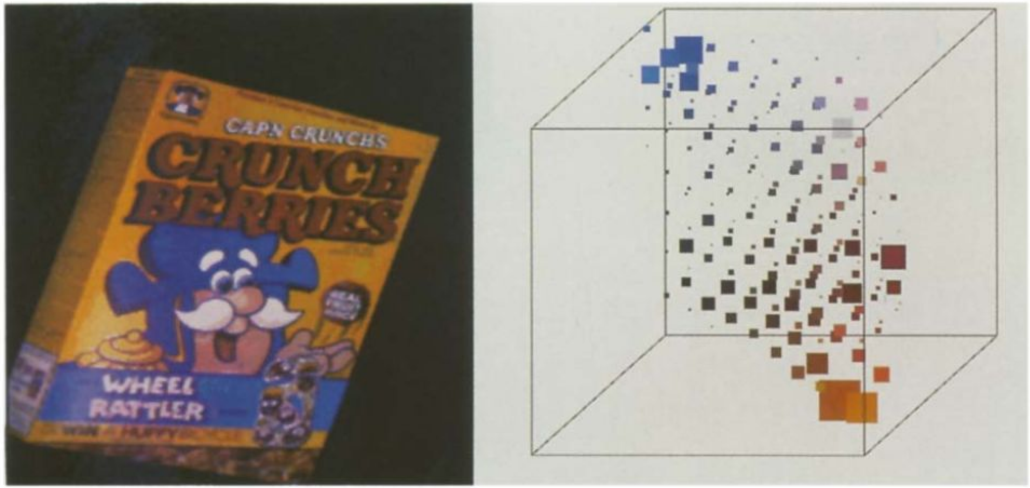


Fig. 1. Left: Image of a Crunchberries cereal box. Right: Three dimensional color histogram of the Crunchberries image with the black background substrated.

↑ 16M colors

↑ 7 colors (+ white bg)

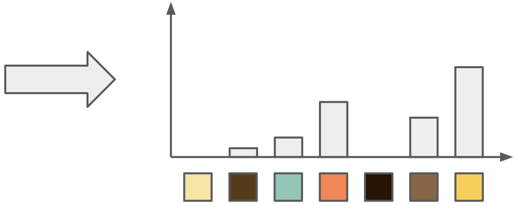
One possible result on the *Twin it!* poster

Color histograms: Step by step

2: Histogram computation

You already know it.

(Normalize it.)



Color histograms: Step by step

3: Descriptor comparison

Many distribution metrics.

Cosine, Euclidean, Chebyshev…

$$1 - \frac{u \cdot v}{||u||_2 ||v||_2}.$$

Read, try, compare, learn!

Two histograms =

Two 1-D vectors!

```
from scipy.spatial.distance import …
```

Distance functions between two numeric vectors `u` and `v`. Computing distances over a large collection of vectors is inefficient for these functions. Use `pdist` for this purpose.

braycurtis(u, v[, w])	Compute the Bray-Curtis distance between two 1-D arrays.
canberra(u, v[, w])	Compute the Canberra distance between two 1-D arrays.
chebyshev(u, v[, w])	Compute the Chebyshev distance.
cityblock(u, v[, w])	Compute the City Block (Manhattan) distance.
correlation(u, v[, w, centered])	Compute the correlation distance between two 1-D arrays.
cosine(u, v[, w])	Compute the Cosine distance between 1-D arrays.
euclidean(u, v[, w])	Computes the Euclidean distance between two 1-D arrays.
jensenshannon(p, q[, base])	Compute the Jensen-Shannon distance (metric) between two 1-D probability arrays.
mahalanobis(u, v, VI)	Compute the Mahalanobis distance between two 1-D arrays.
minkowski(u, v[, p, w])	Compute the Minkowski distance between two 1-D arrays.
seuclidean(u, v, V)	Return the standardized Euclidean distance between two 1-D arrays.
sqeuclidean(u, v[, w])	Compute the squared Euclidean distance between two 1-D arrays.
wminkowski(u, v, p, w)	Compute the weighted Minkowski distance between two 1-D arrays.

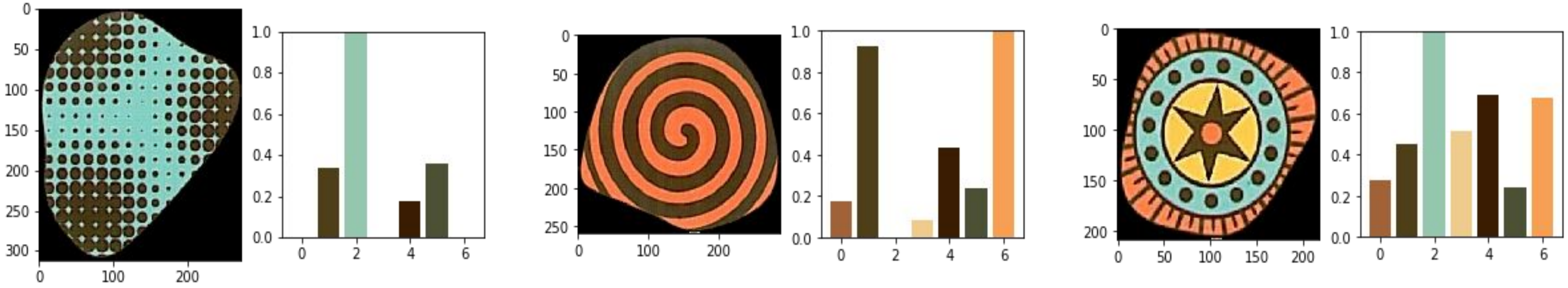
Discussion

Can you think of other global descriptors we could have implemented for the *Twin it!* case?

Next practice session

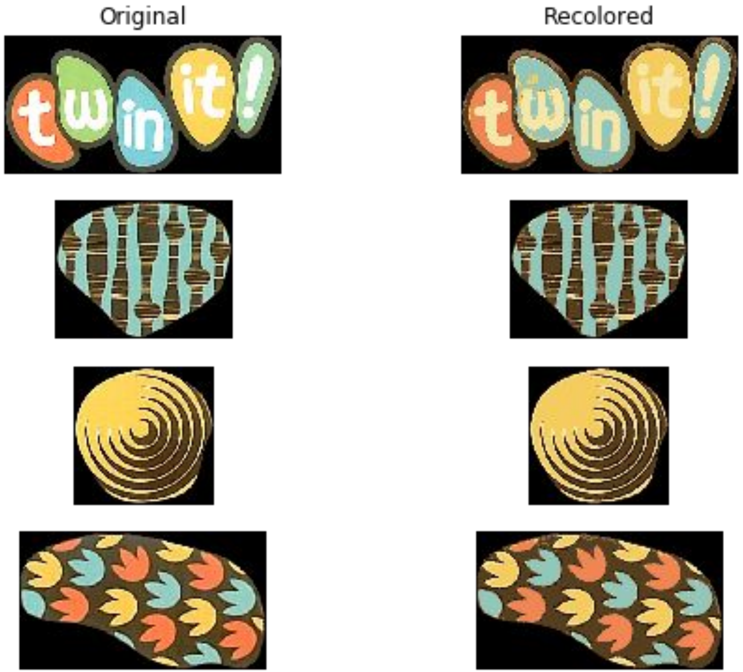
Twin it!, again, with a slightly more elaborated approach:

1. **Pre-select bubbles based on their colors ⇒ Color histograms**



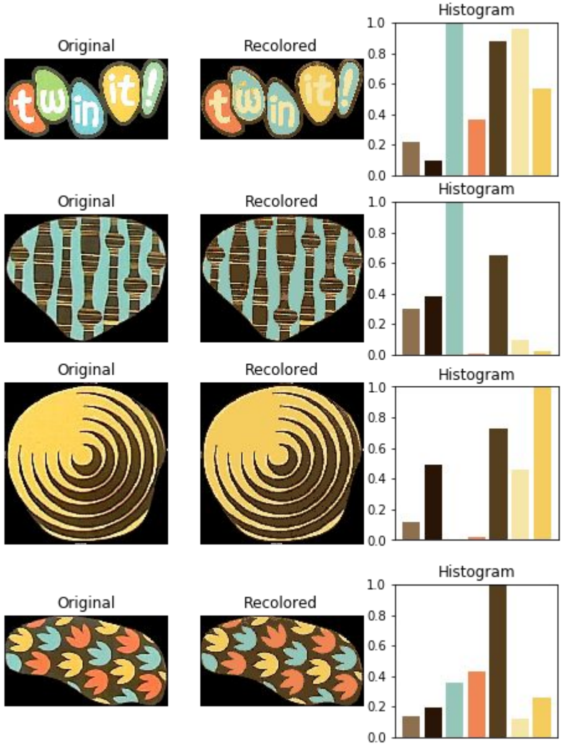
Color histogram: In details

1.1. Color quantization: reduce the colors of the bubbles.



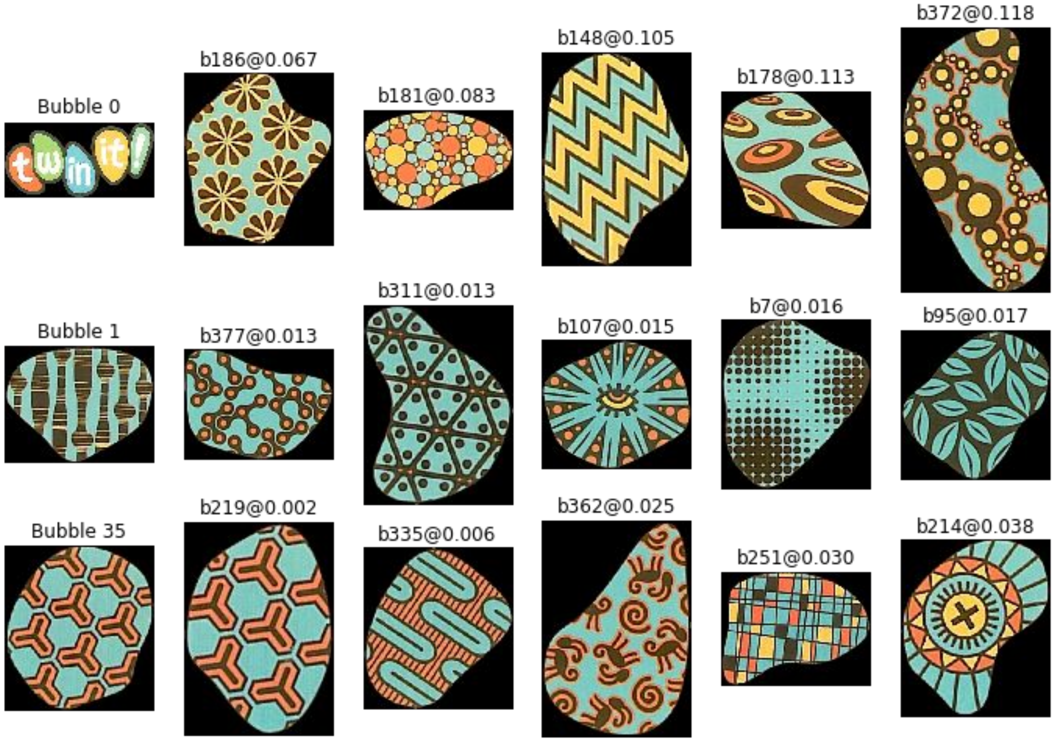
Color histogram: In details

1.2. Compute the color histogram of each bubble.



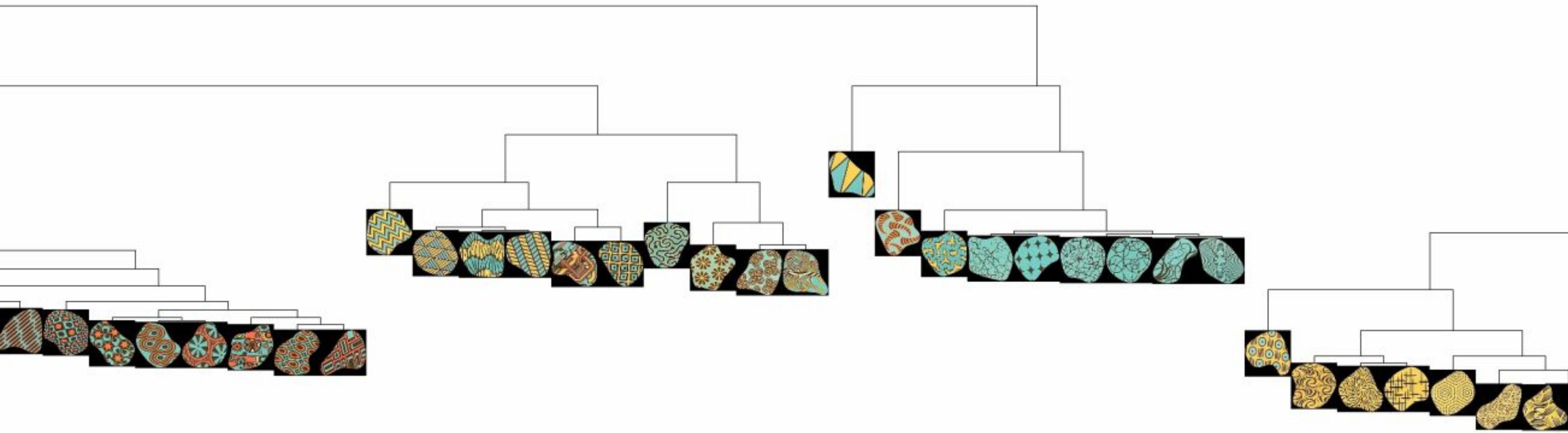
Color histogram: In details

1.3. Compute the distance matrix between each bubble, using its color histogram.



Color histogram: In details

1.4. Visualize the bubbles in an interesting way using hierarchical clustering.



Other global image descriptors

Oliva & Torralba 2001

More global descriptors

GIST of a scene:

- Oliva, Torralba, “Modeling the shape of the scene: a holistic representation of the spatial envelope”, IJCV’01.
- Douze, Jegou, Sandhawalia, Amsaleg, Schmid, “Evaluation of GIST descriptors for web-scale image search”, CIVR’09.

CENTRIST: CENsus Transform hISTogram

- Wu, Rehg, “CENTRIST: a visual descriptor for scene categorization”, TPAMI’11.

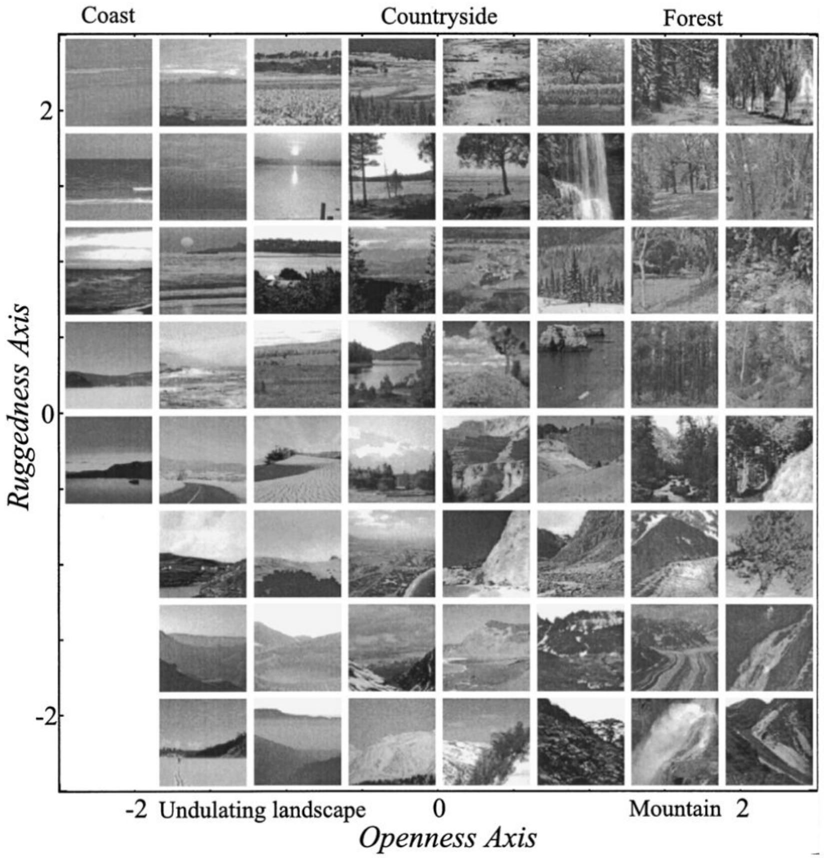


Figure 15. Organization of natural scenes according to the openness and ruggedness properties estimated by the WDSTs.

Global descriptors: drawback

According to F. Perronnin:

Highly efficient to compute and to match

⇒ **perfect in theory**

But **robustness vs informativeness tradeoff is hard to set**

(personal conclusion):

- Approaches based on **global image descriptors** are confined to **near-duplicate detection** applications until now.
- Modern search engines use local representations and leverage them.