TDS3651
Visual Information Processing

Textures

Lecture 7

Faculty of Computing and Informatics
Multimedia University

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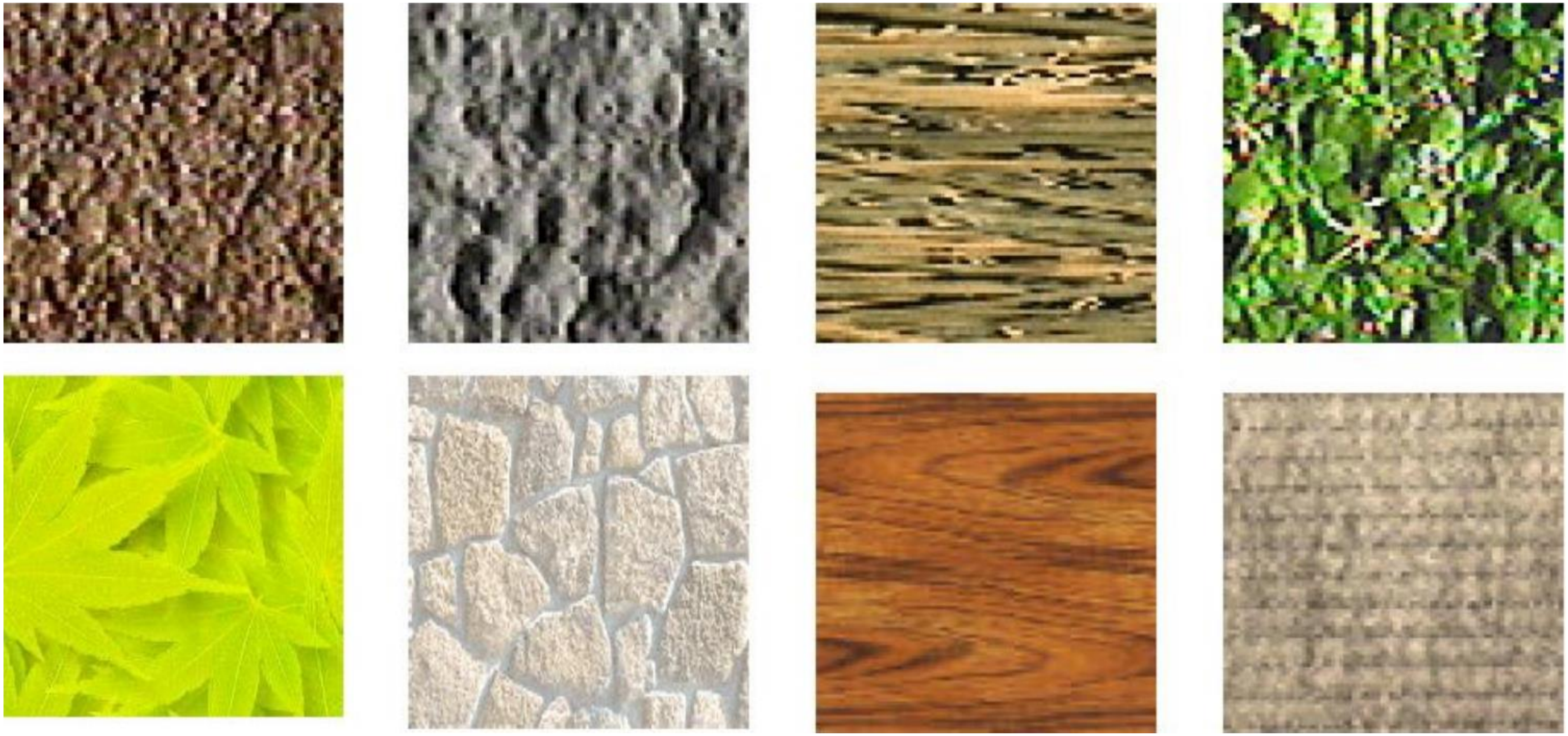
Some graphics and materials are taken from UTexas at Austin CS376 & CS381V notes, Stanford Uni's CS131 notes and Gonzalez & Wood's DIP textbook

Lecture Outline

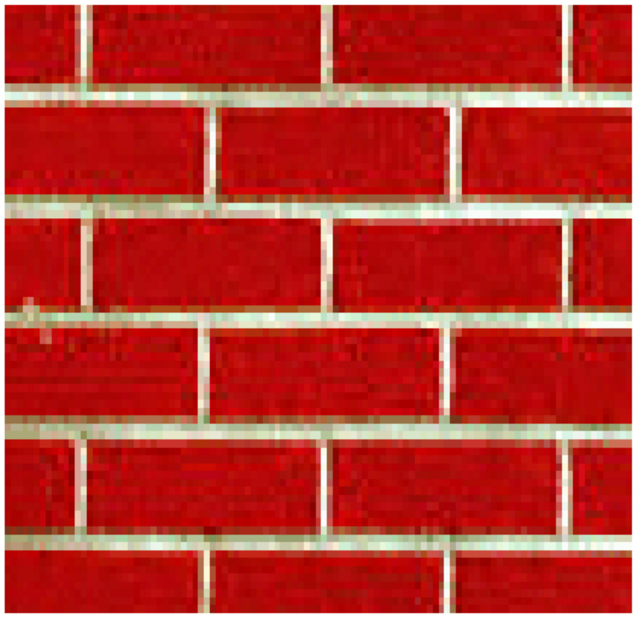
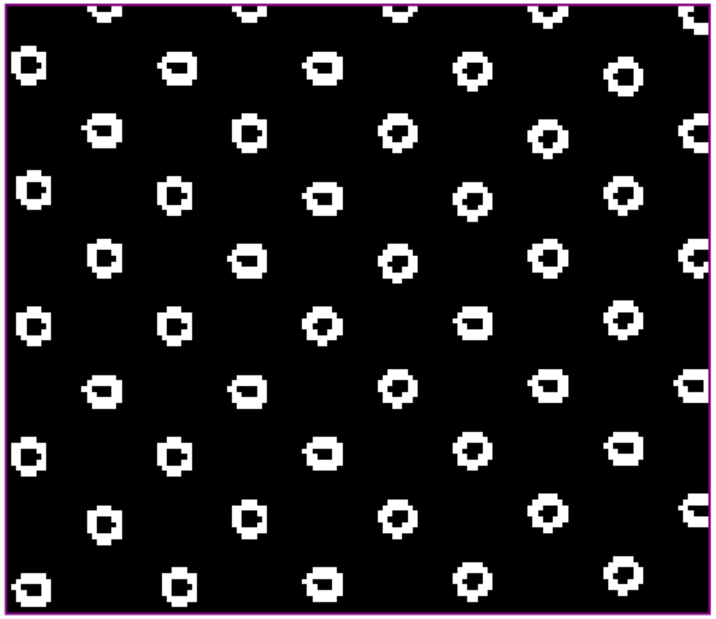
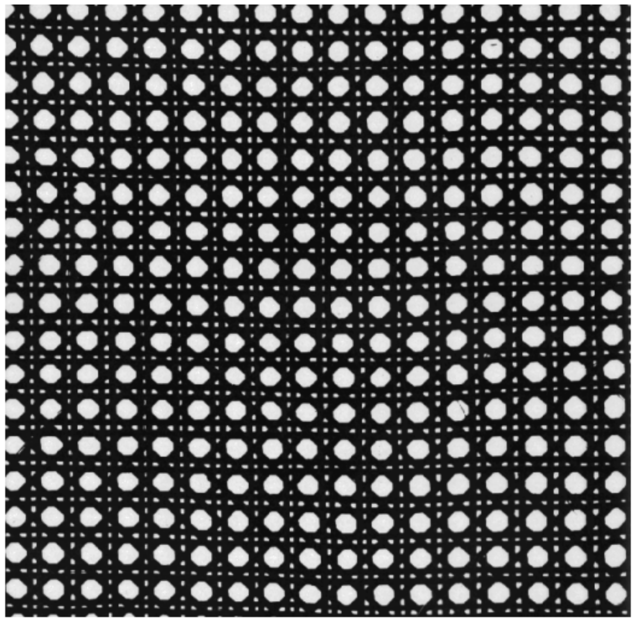
- Textures
  - Defining textures in images
  - Texture representation, Filter bank
- Clustering
  - K-means clustering
  - Using clustering to form histograms for texture feature occurrences
- Applications

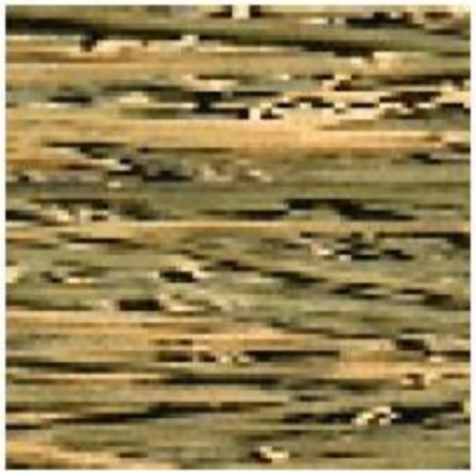
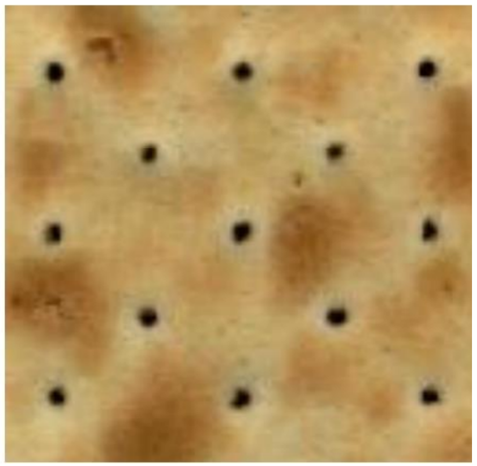
What defines a texture?

Textures



Regular & Irregular patterns

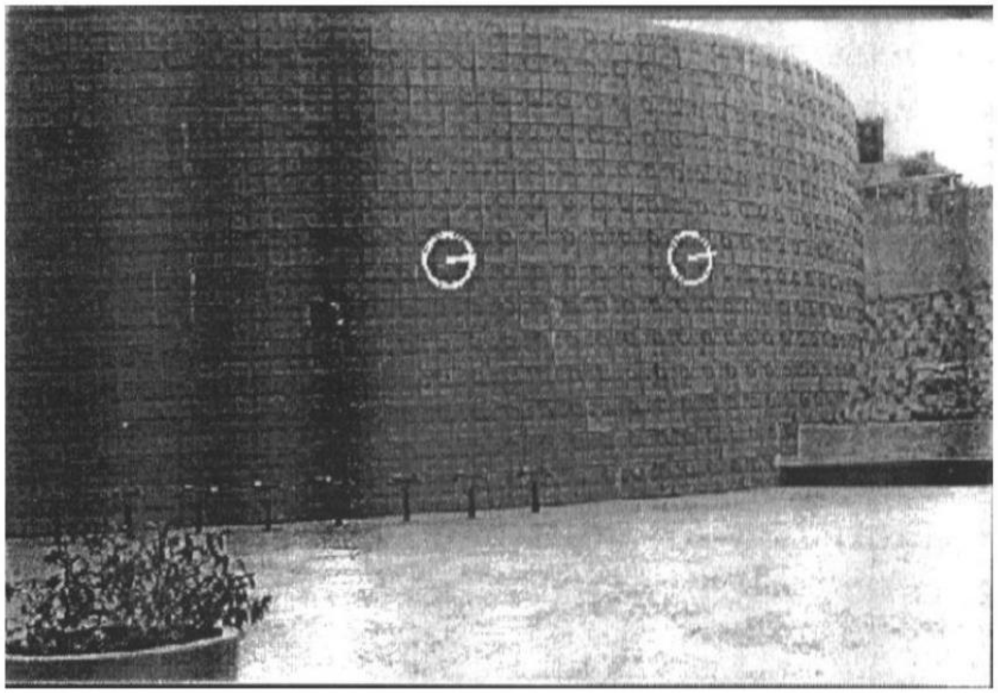



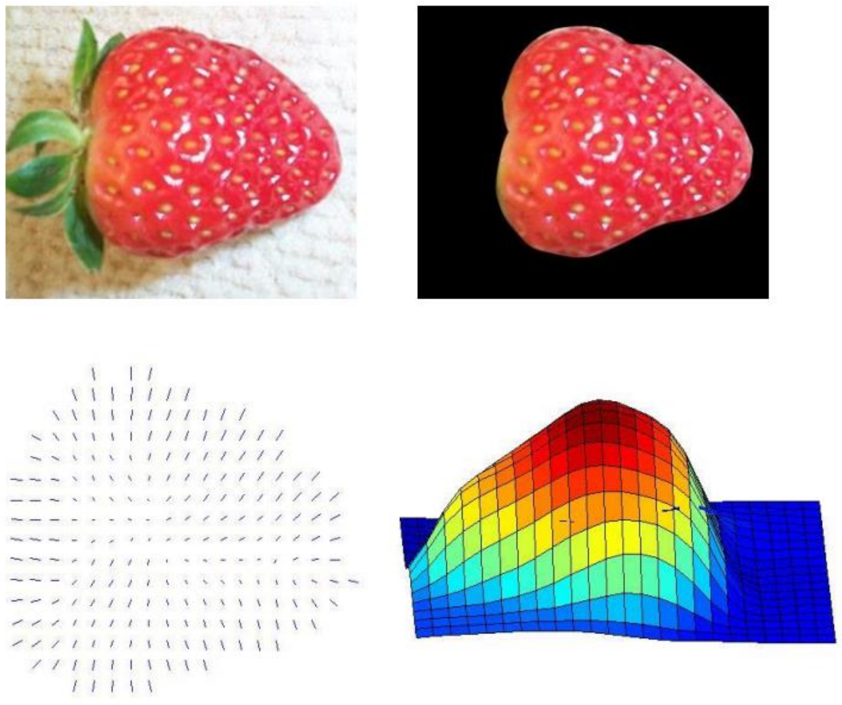
Texture-related tasks

- **Shape from texture**
  - Estimate surface orientation or shape from image texture
- **Segmentation/classification** from texture cues
  - Analyze, represent texture
  - Group image regions with consistent texture
- **Synthesis**
  - Generate new texture patches/images given some examples

Texture-related tasks

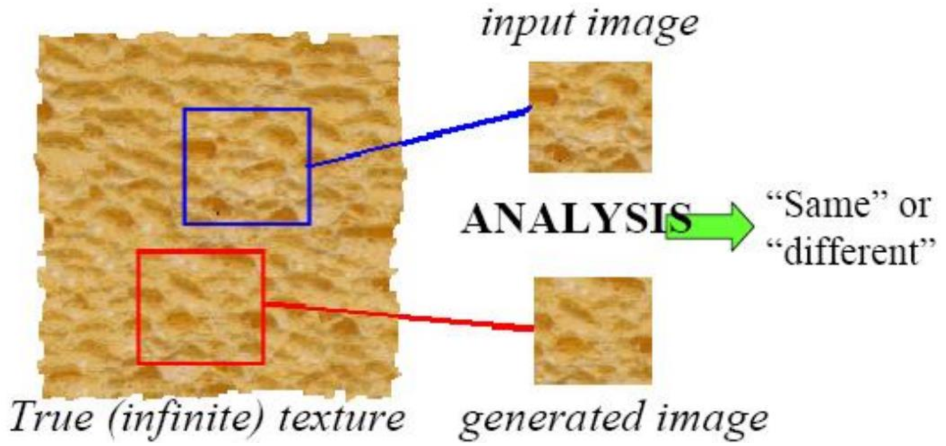
- **Shape from texture**
  - Estimate surface orientation or shape from image texture

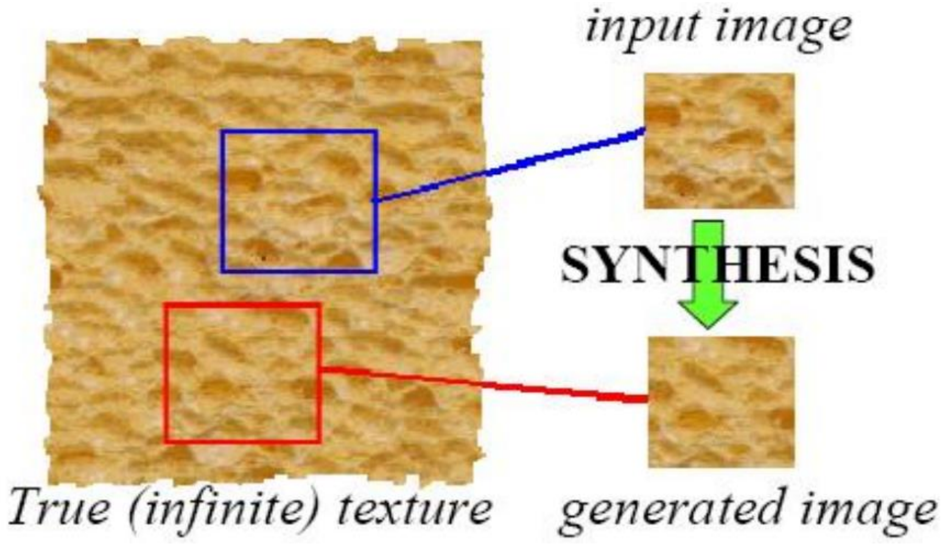




Analysis vs. Synthesis

- **Why** analyse texture?
- **Why** synthesize texture?

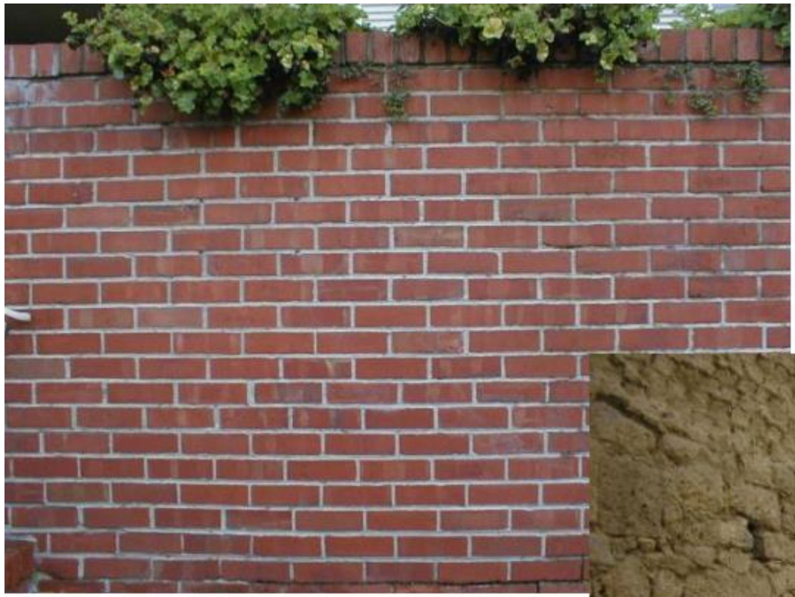


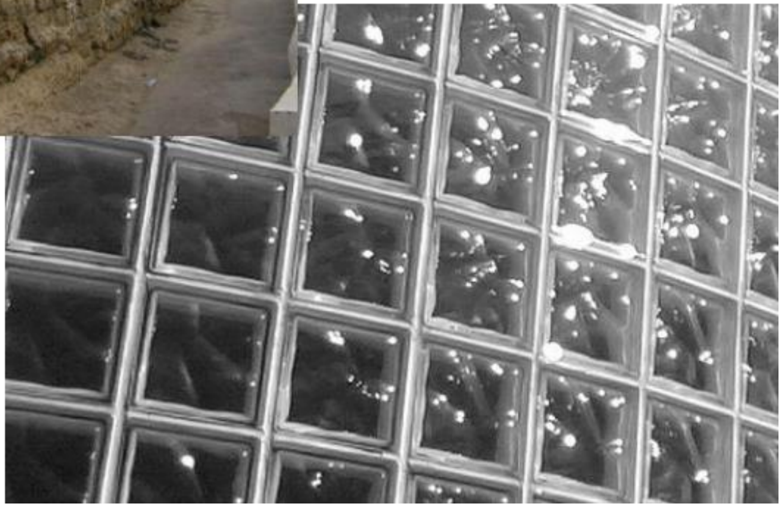


Texture-related tasks

- **Shape from texture**
  - Estimate surface orientation or shape from image texture
- **Segmentation/classification** from texture cues
  - Analyze, represent texture
  - Group image regions with consistent texture
- **Synthesis**
  - Generate new texture patches/images given some examples

Textures from walls

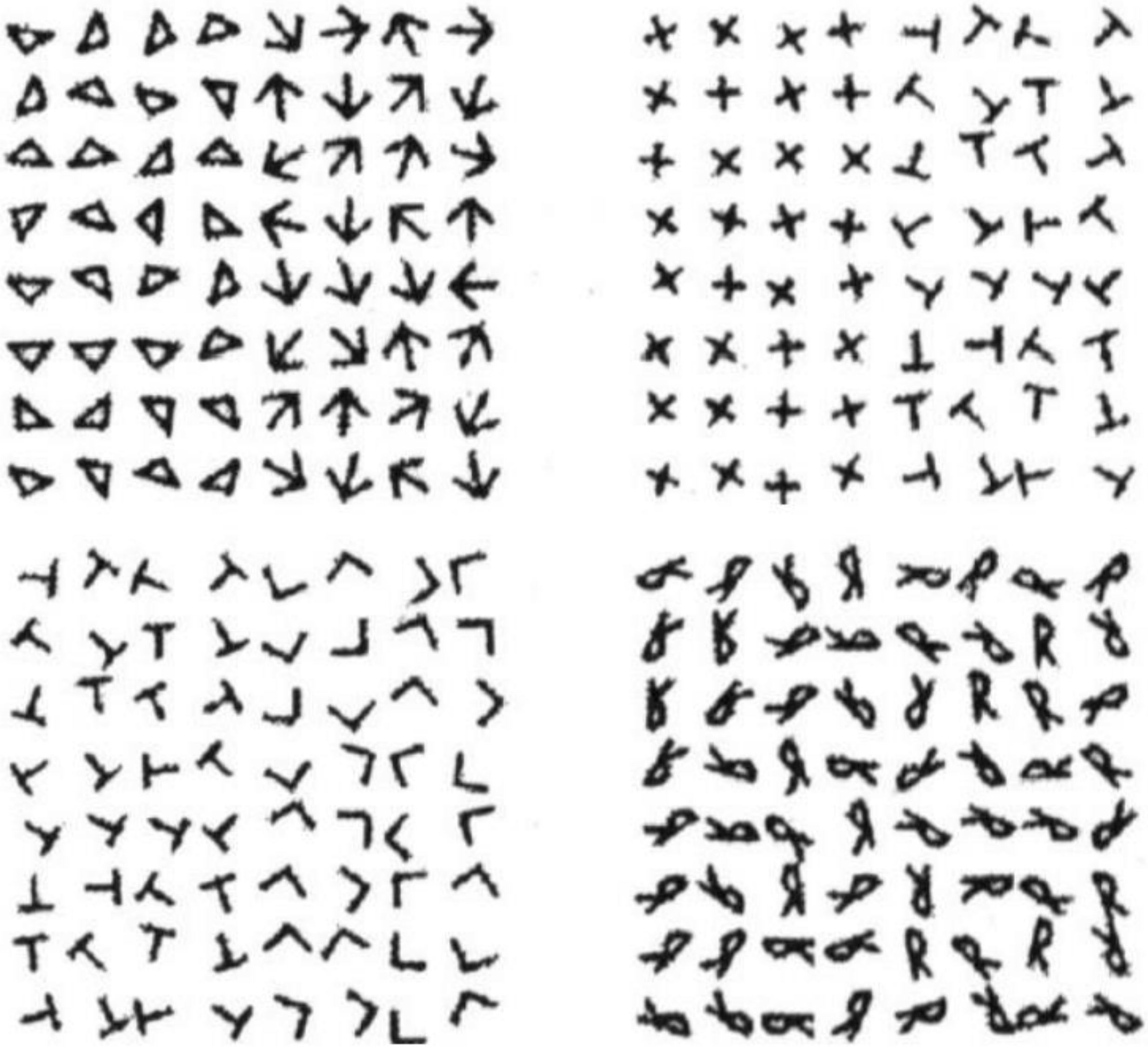




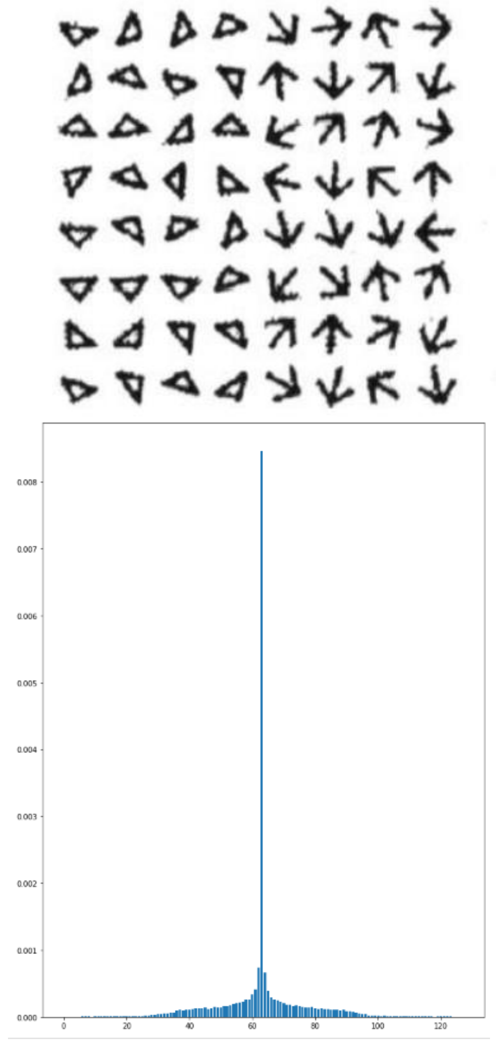
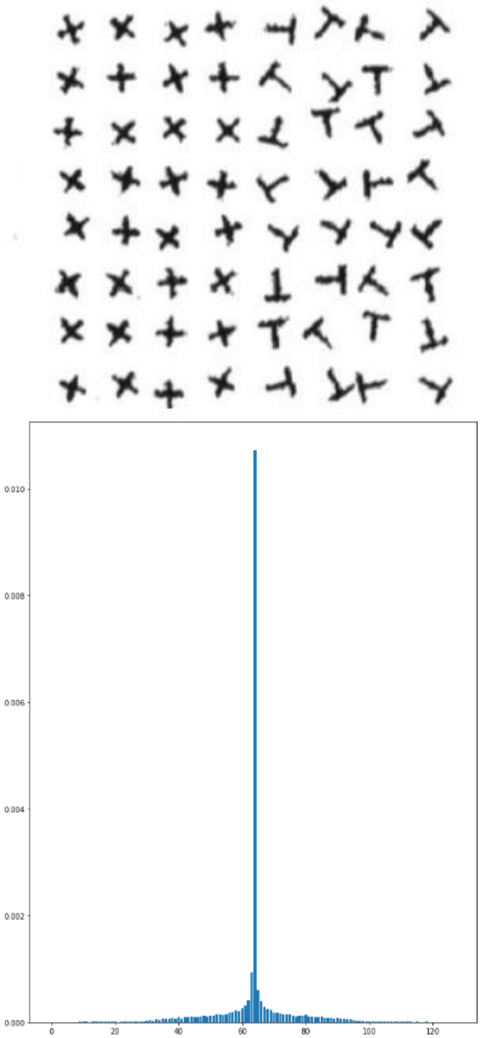
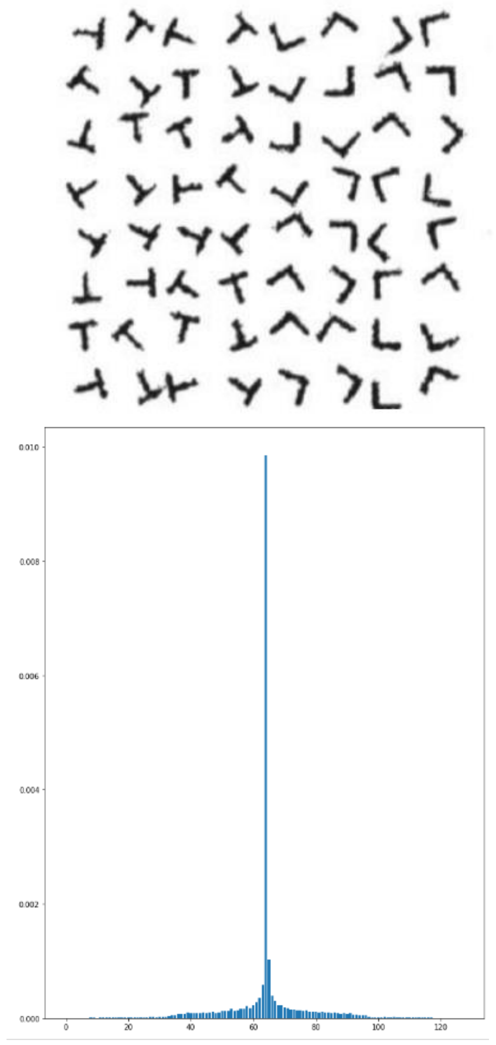
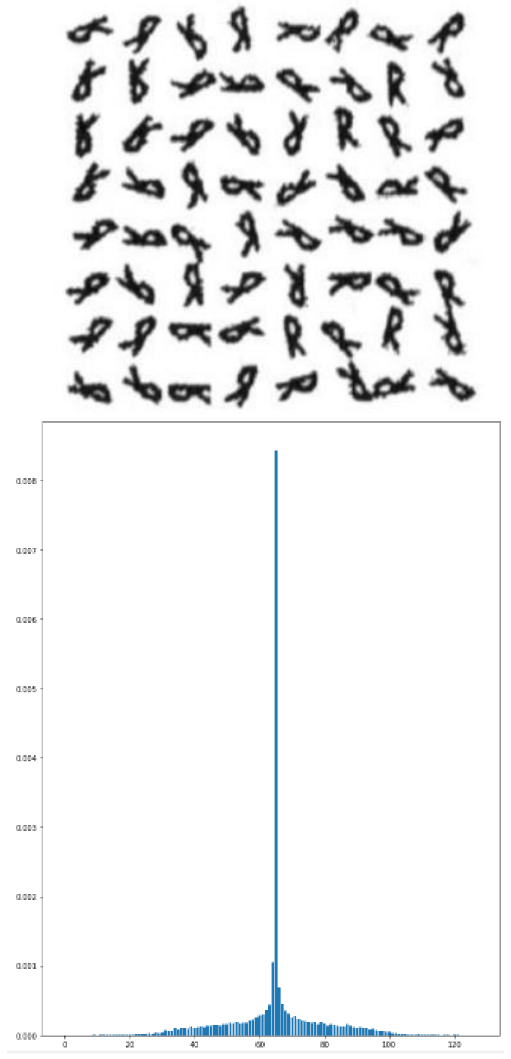
Textures from animals

Are edges sufficient?

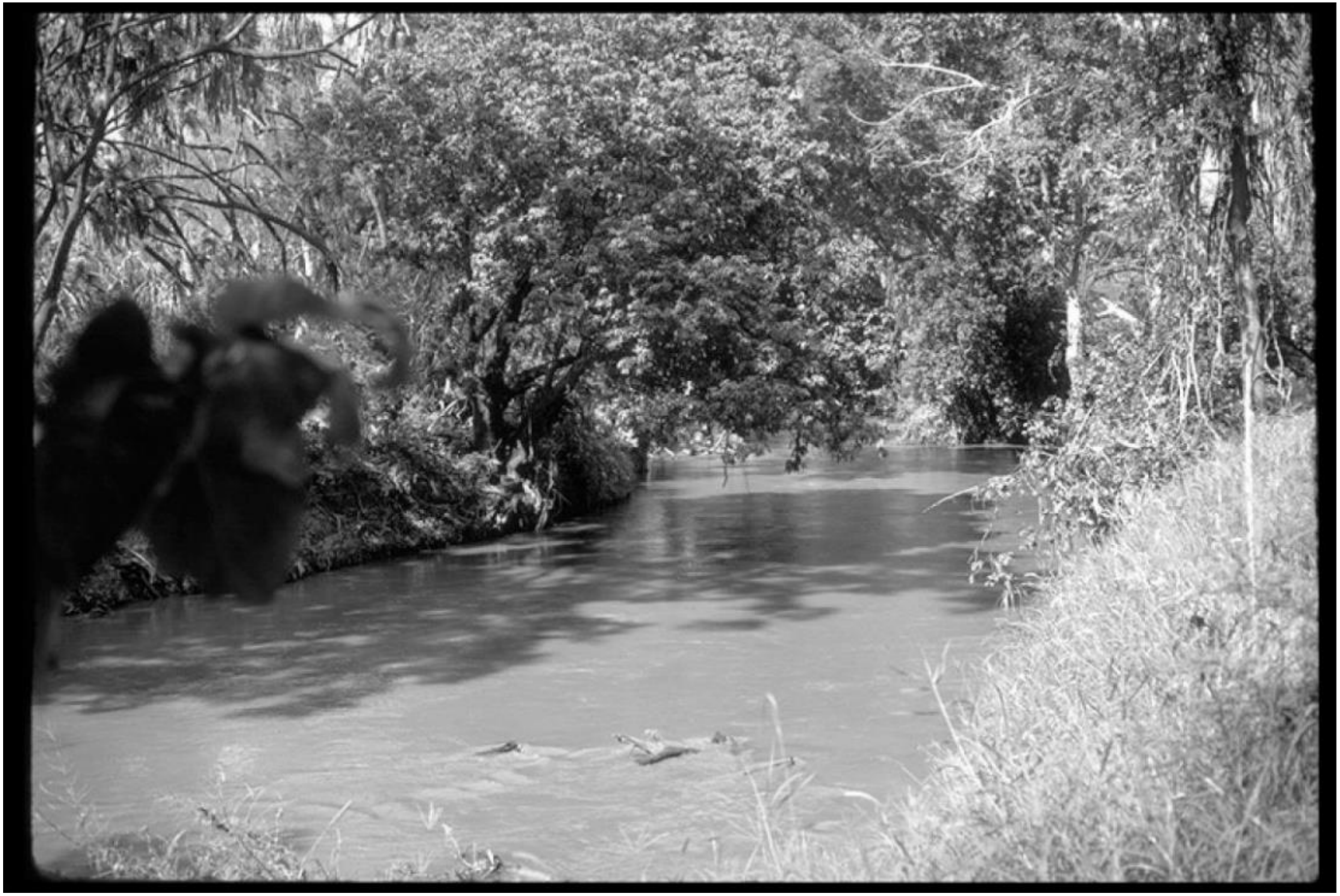
- What kind of response will we get with an edge detector for these images?
- Is it **good enough** to "represent" the image content?



Are edges sufficient?

What about this image?



Why analyse texture?

- **Important to perception:**
  - Indicates material's properties
  - Appearance cue, especially if shape is similar (e.g. orange vs. apple)

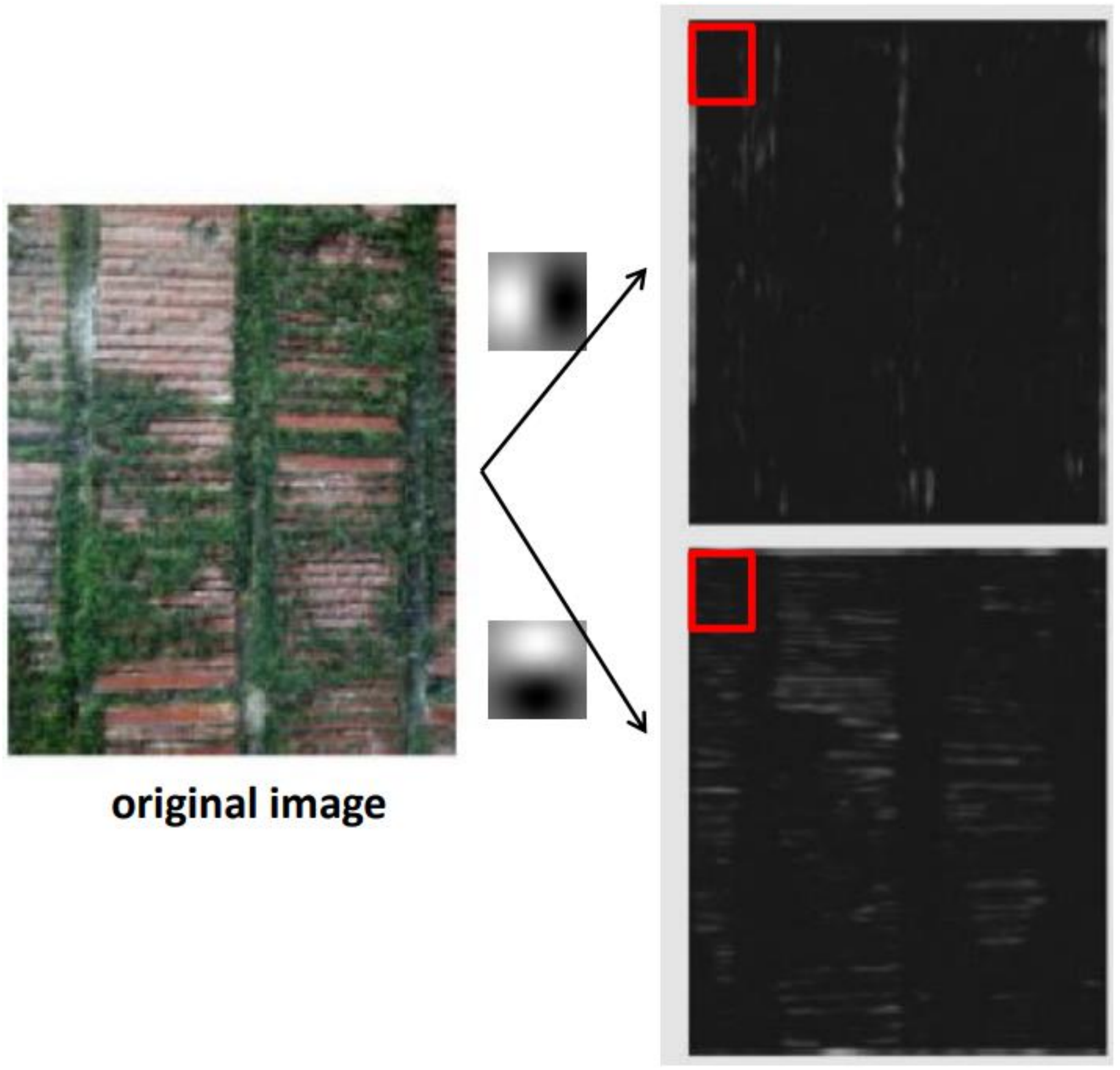
- In technical terms…
  - **Representation**-wise, we want a feature one step above "basic building blocks" of filter outputs, edges, etc.

How should we represent these textures as data?

Texture Representation

- Textures are made up of **repeated local patterns**, so
  - **Find** these “patterns”
    - Use filters that LOOK like patterns (spots, bars, raw patches, etc.)
    - Consider magnitude of response of these patterns
  - **Describe** their statistics within each local window (or “neighbourhood”)
    - Mean, standard deviation
    - (and at a higher level..) Histogram of feature occurrences

Texture Representation

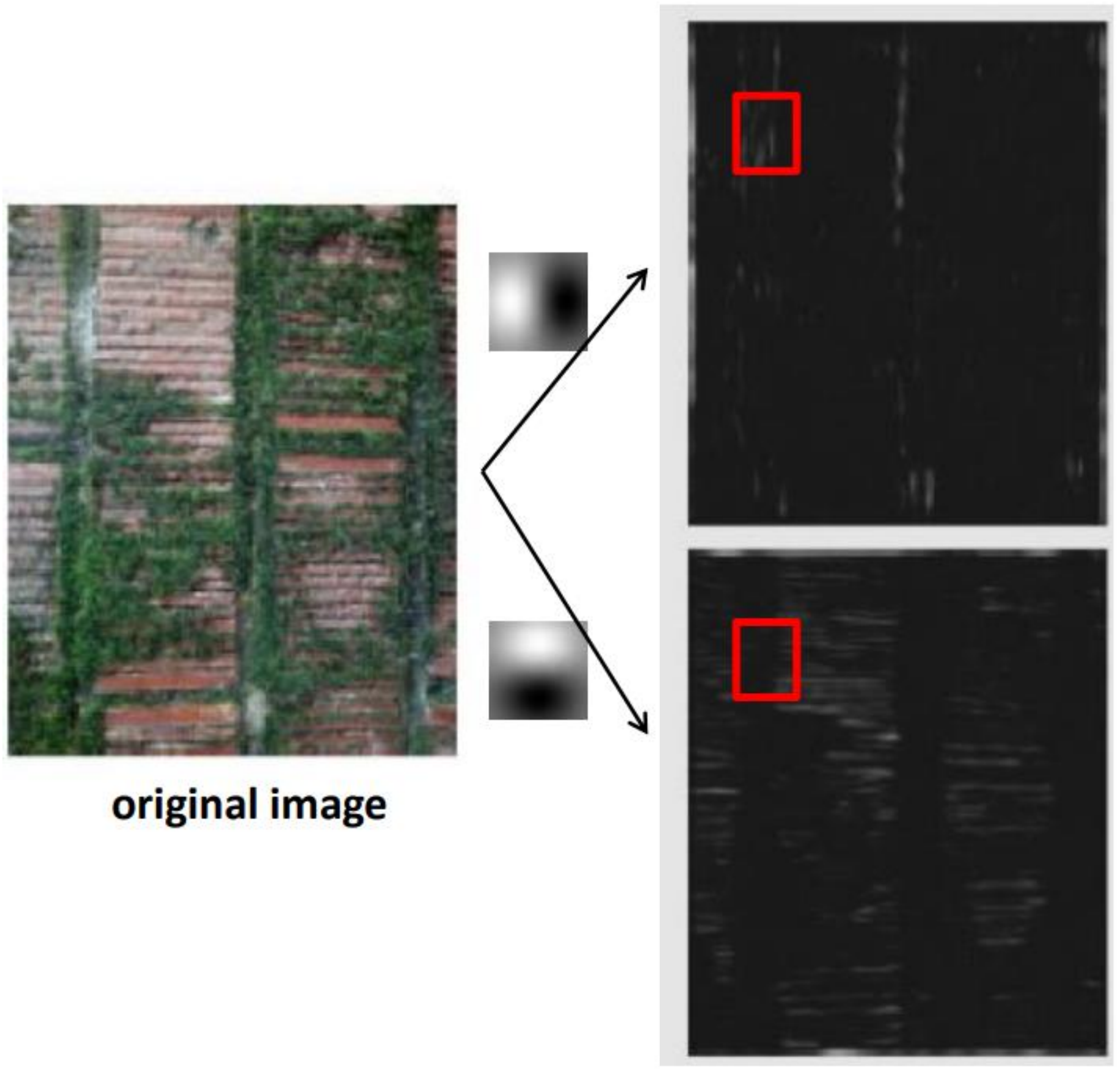


	Mean d/dx value	Mean d/dy value
Win. #1	4	10

⋮

statistics to summarize patterns in small windows

Texture Representation

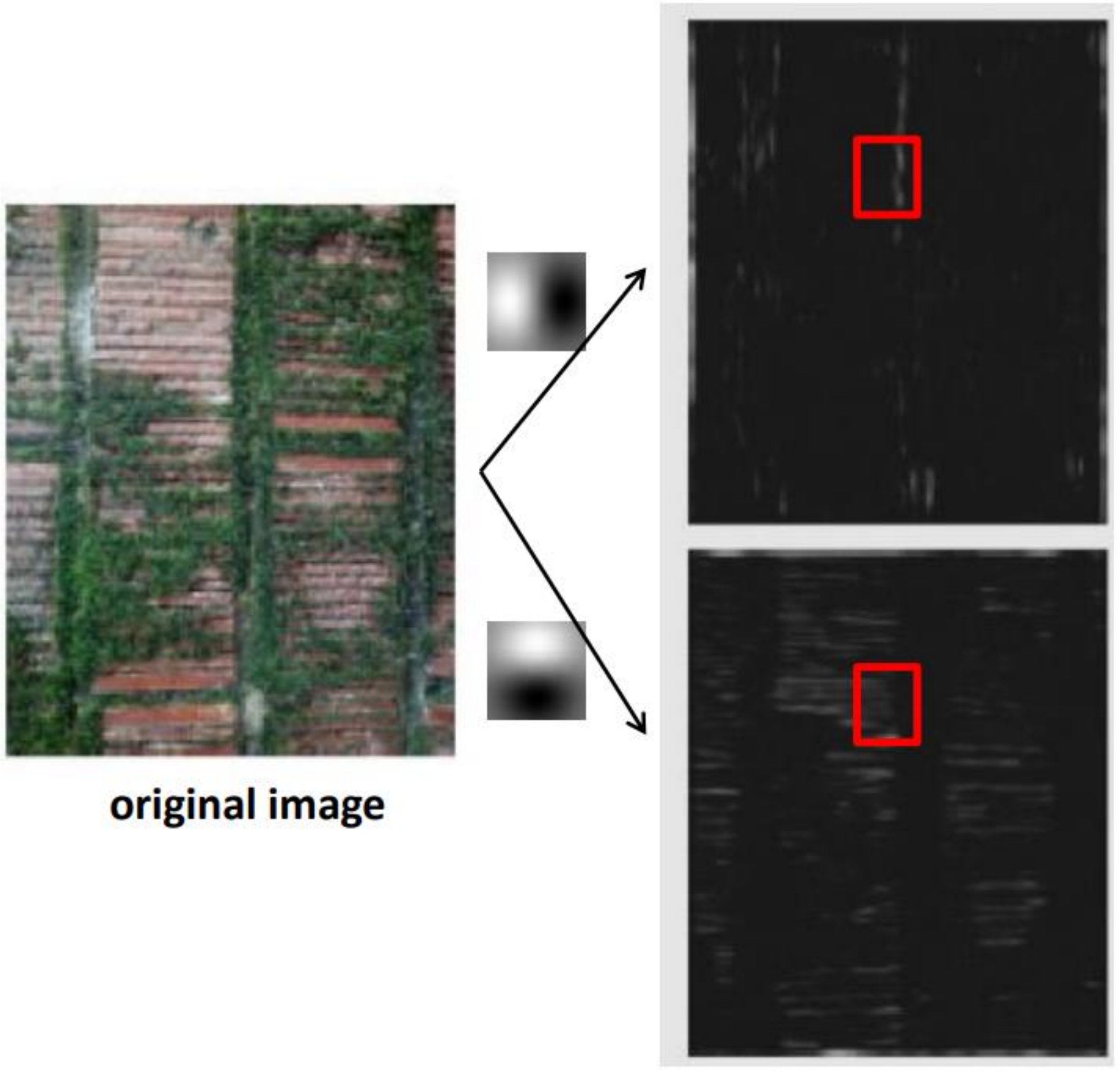


	Mean d/dx value	Mean d/dy value
Win. #1	4	10
Win. #2	18	7

⋮

statistics to summarize patterns in small windows

Texture Representation



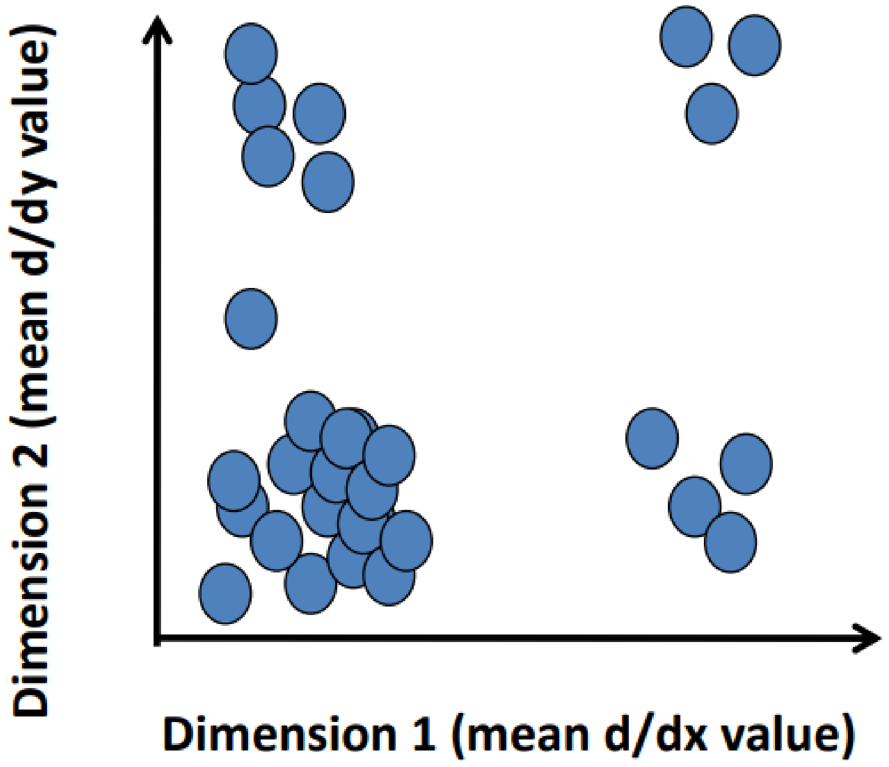
derivative filter responses, squared

	Mean d/dx value	Mean d/dy value
Win. #1	4	10
Win. #2	18	7
⋮	⋮	⋮
Win. #9	20	20

⋮

statistics to summarize patterns in small windows

Texture Representation

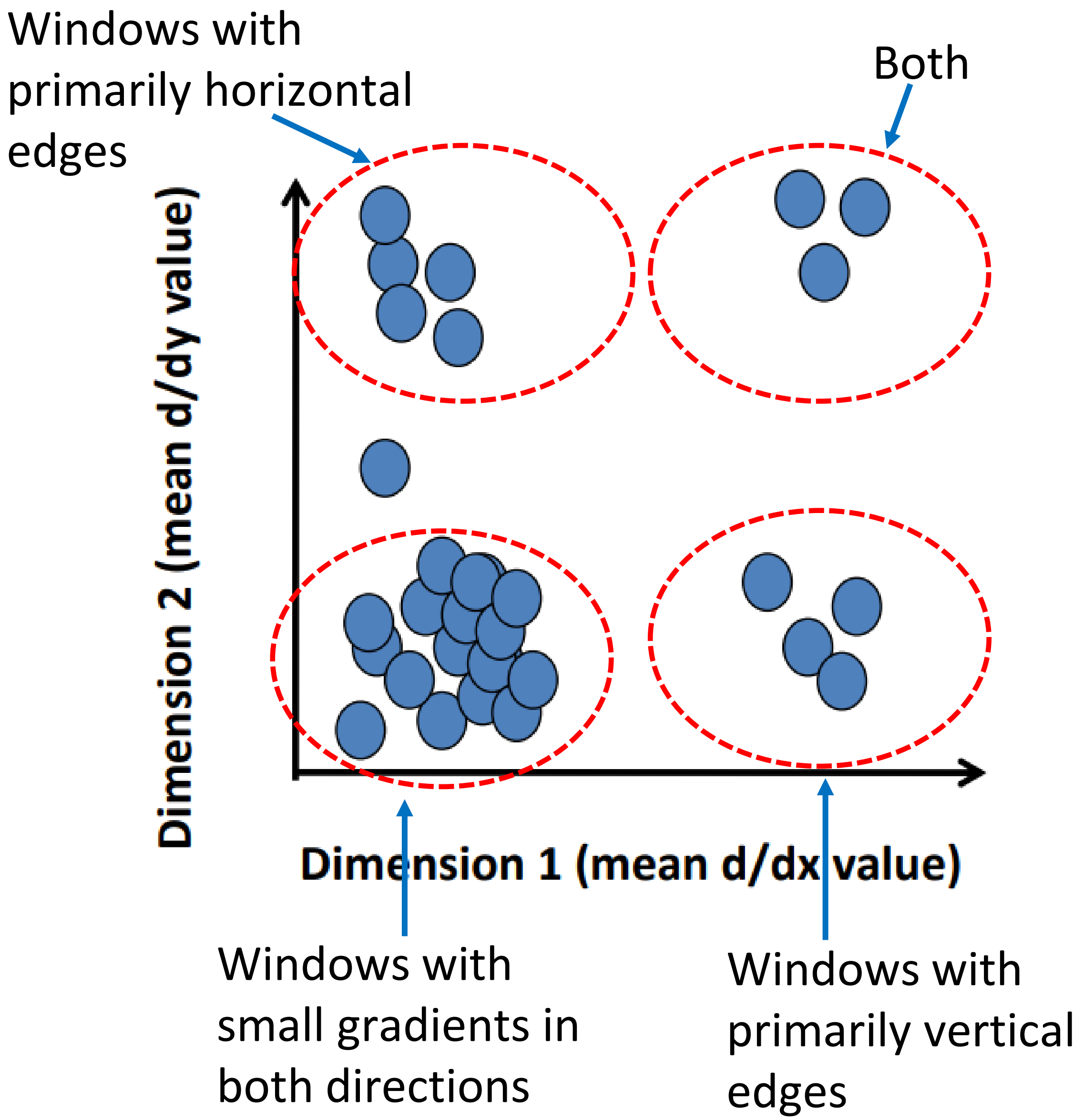


	Mean d/dx value	Mean d/dy value
Win. #1	4	10
Win. #2	18	7
⋮	⋮	⋮
Win. #9	20	20

⋮

statistics to summarize patterns in small windows

Texture Representation



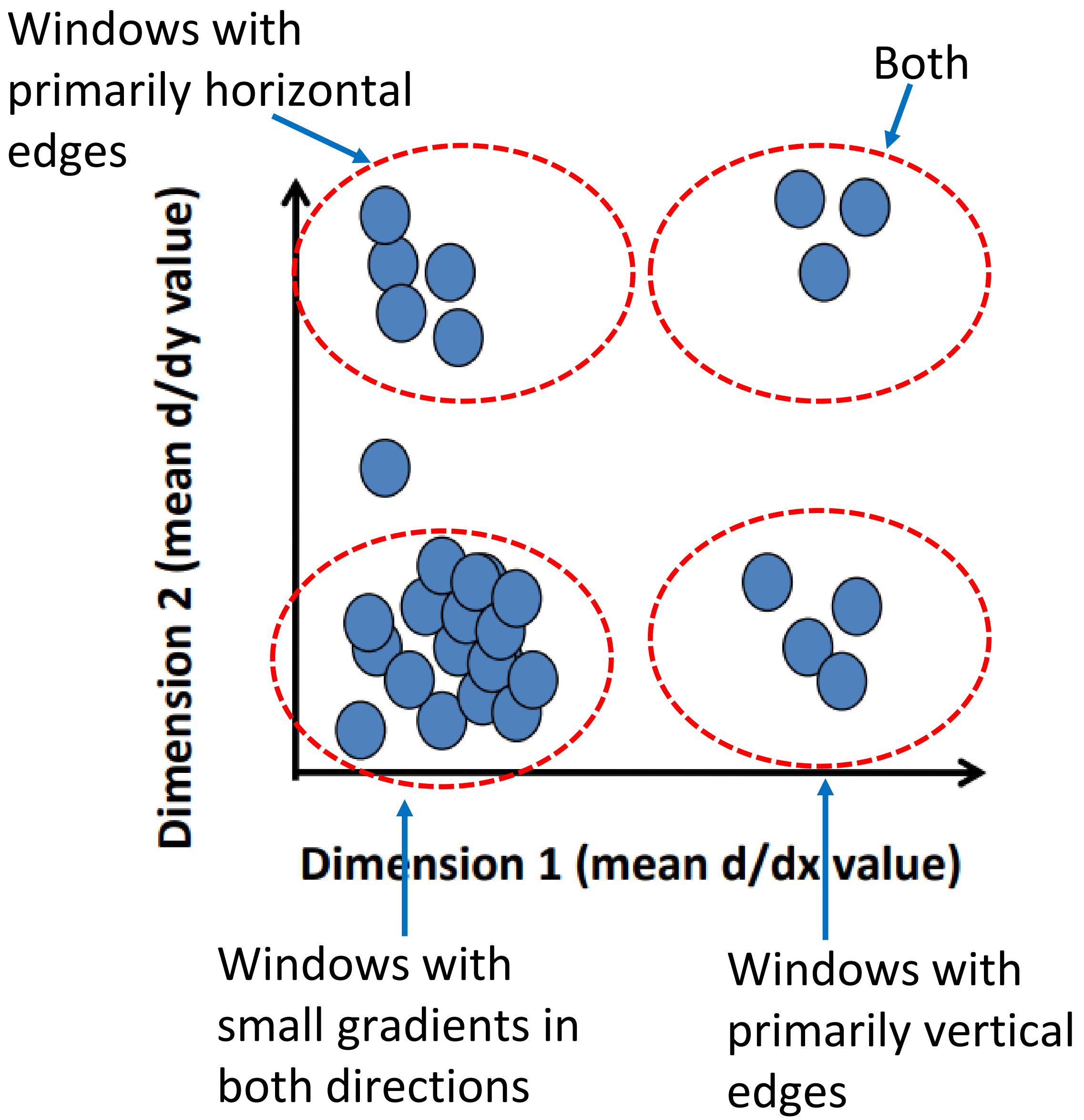
Windows with primarily horizontal edges
Both
Dimension 2 (mean d/dy value)
Dimension 1 (mean d/dx value)
Windows with small gradients in both directions
Windows with primarily vertical edges

	Mean d/dx value	Mean d/dy value
Win. #1	4	10
Win. #2	18	7
⋮	⋮	⋮
Win. #9	20	20

⋮

statistics to summarize patterns in small windows

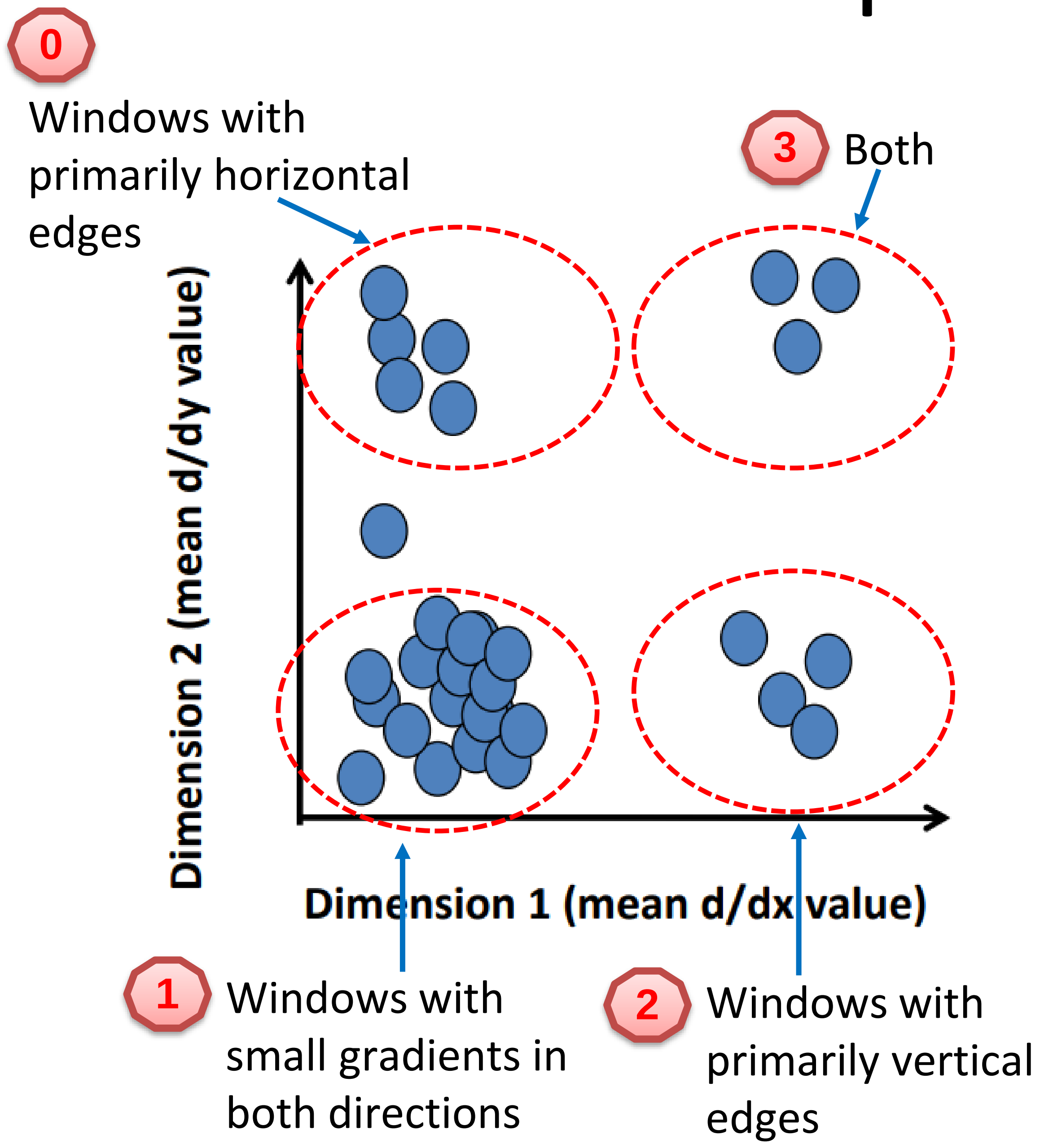
Texture Representation



There are 4 types of textures defined here

Think of a way how we can represent each image pixel with only these 4 texture features…

Texture Representation

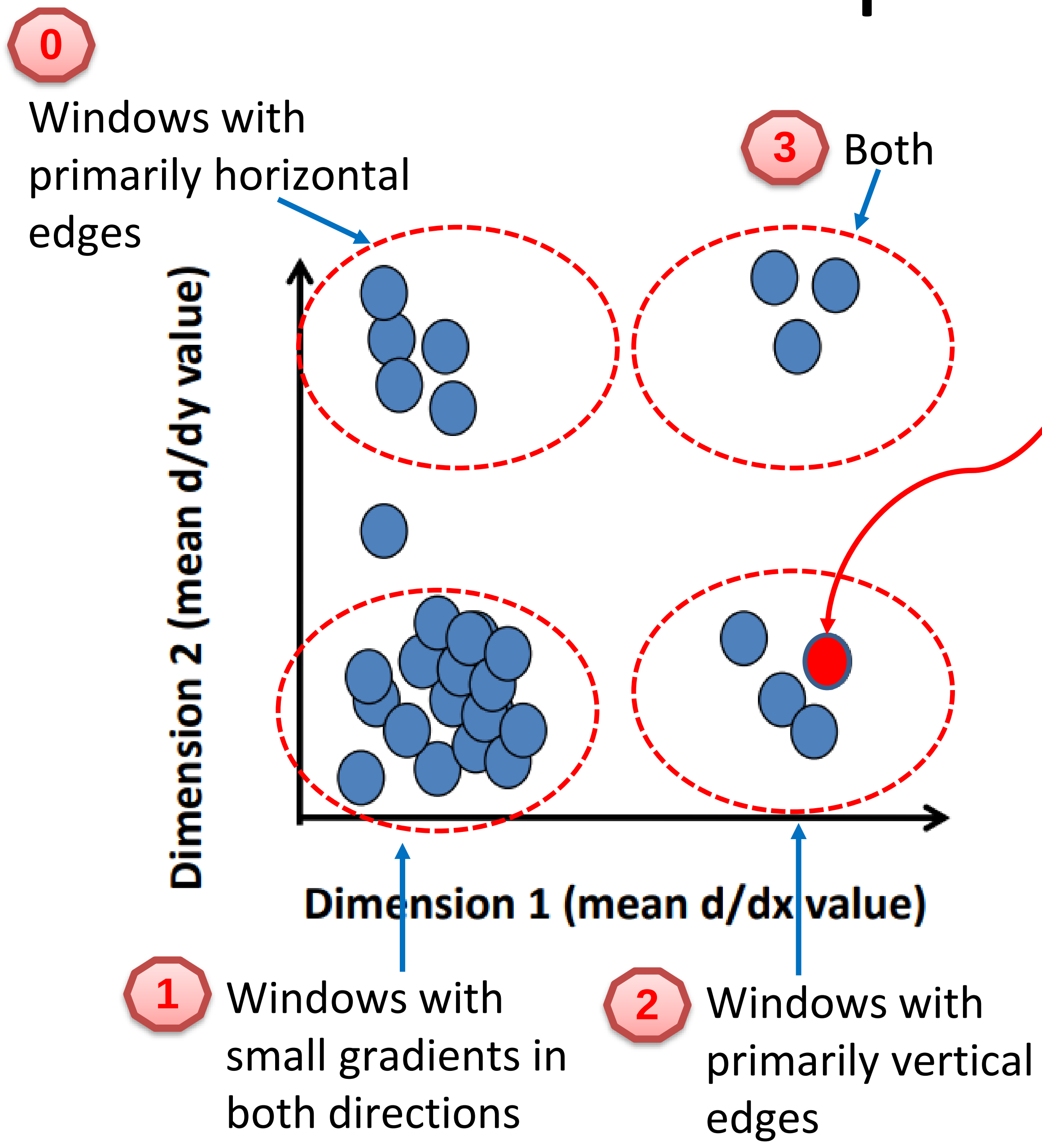

0
Windows with primarily horizontal edges
3
Both
Dimension 2 (mean d/dy value)
Dimension 1 (mean d/dx value)
1
Windows with small gradients in both directions
2
Windows with primarily vertical edges

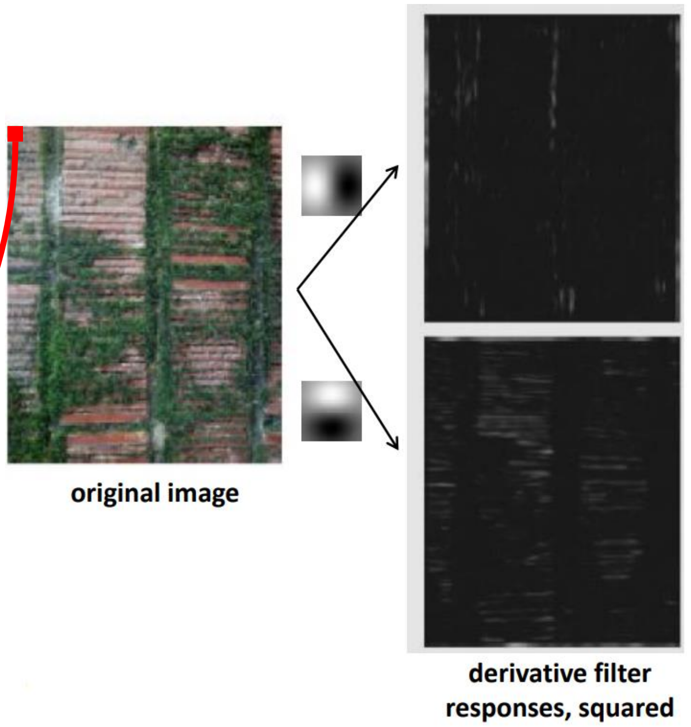
Method #1
Represent each pixel

Label each type of texture (e.g. 0, 1, 2, 3)

Assign the feature values (d/dx and d/dy in this case) to the "nearest" group. Do that for all pixels.

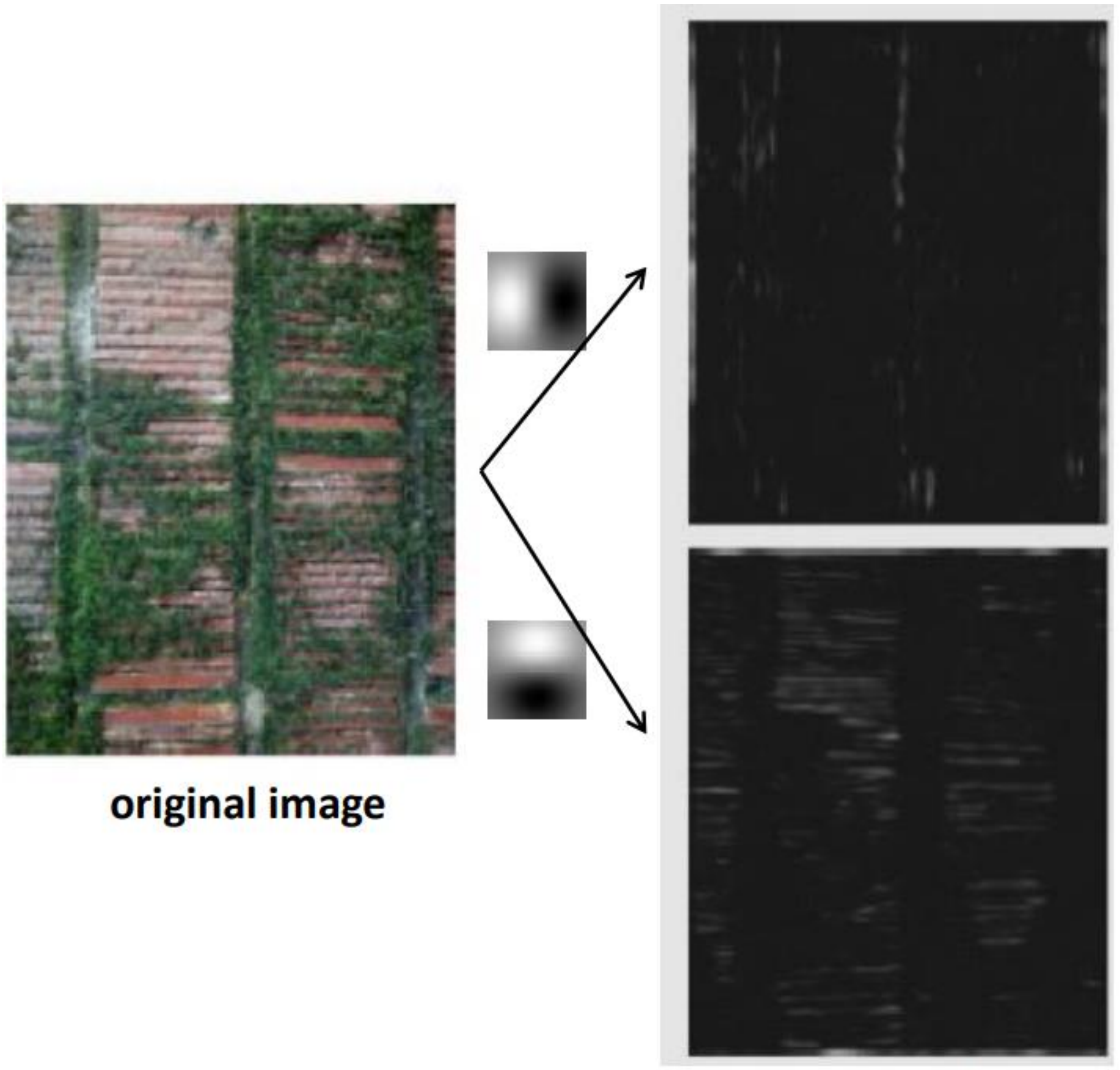
Texture Representation


0
Windows with primarily horizontal edges
3
Both
Dimension 2 (mean d/dy value)
Dimension 1 (mean d/dx value)
1
Windows with small gradients in both directions
2
Windows with primarily vertical edges



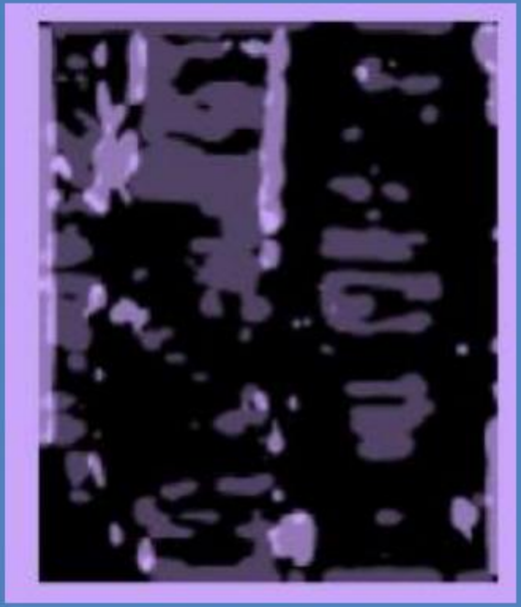
Example:
Pixel marked in red is located in group 2
⇒ Assigned with texture "value" of 2

Texture Representation



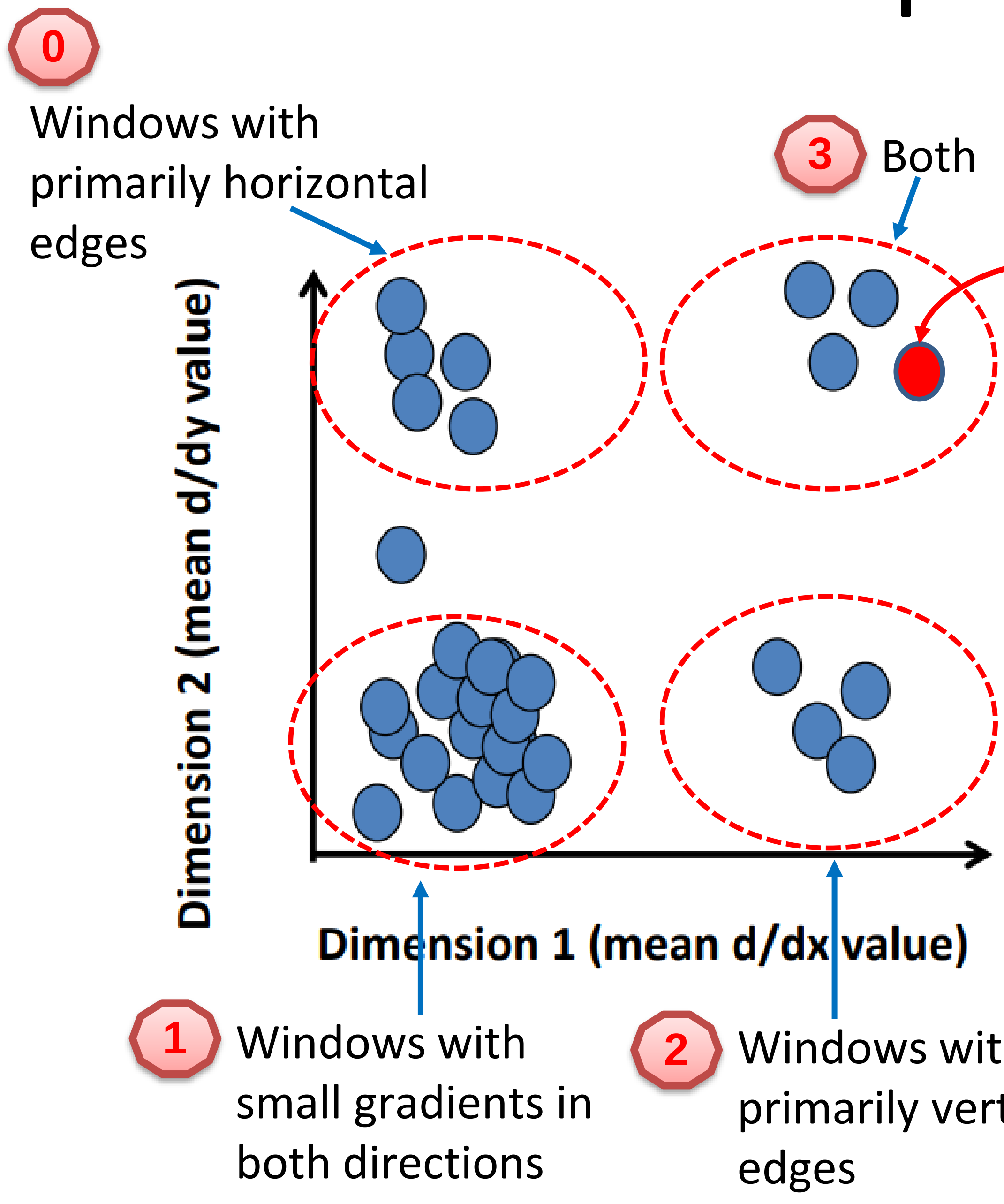
original image

derivative filter responses, squared

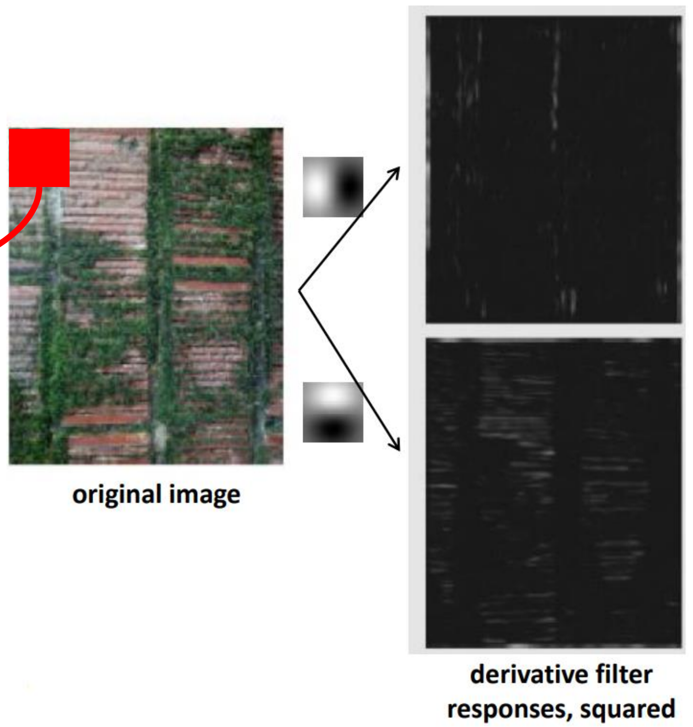


visualization of the assignment to texture "types"

Texture Representation



0
Windows with primarily horizontal edges
3
Both
Dimension 2 (mean d/dy value)
Dimension 1 (mean d/dx value)
1
Windows with small gradients in both directions
2
Windows with primarily vertical edges



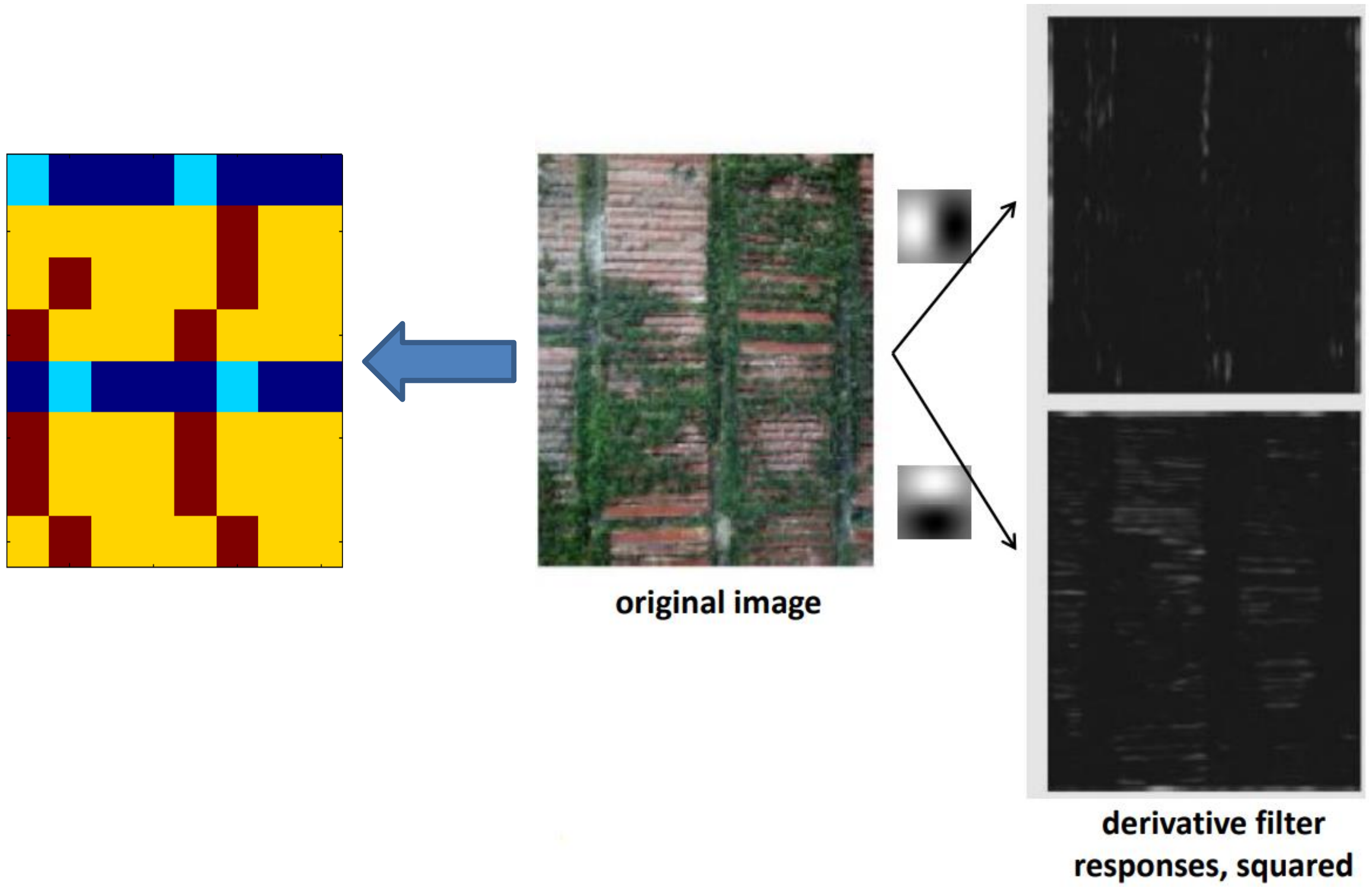
Method #2
Represent each window or "patch"

Example:
Mean gradients of the window marked in red is located in group 3
⇒ Assigned with texture "value" of 3

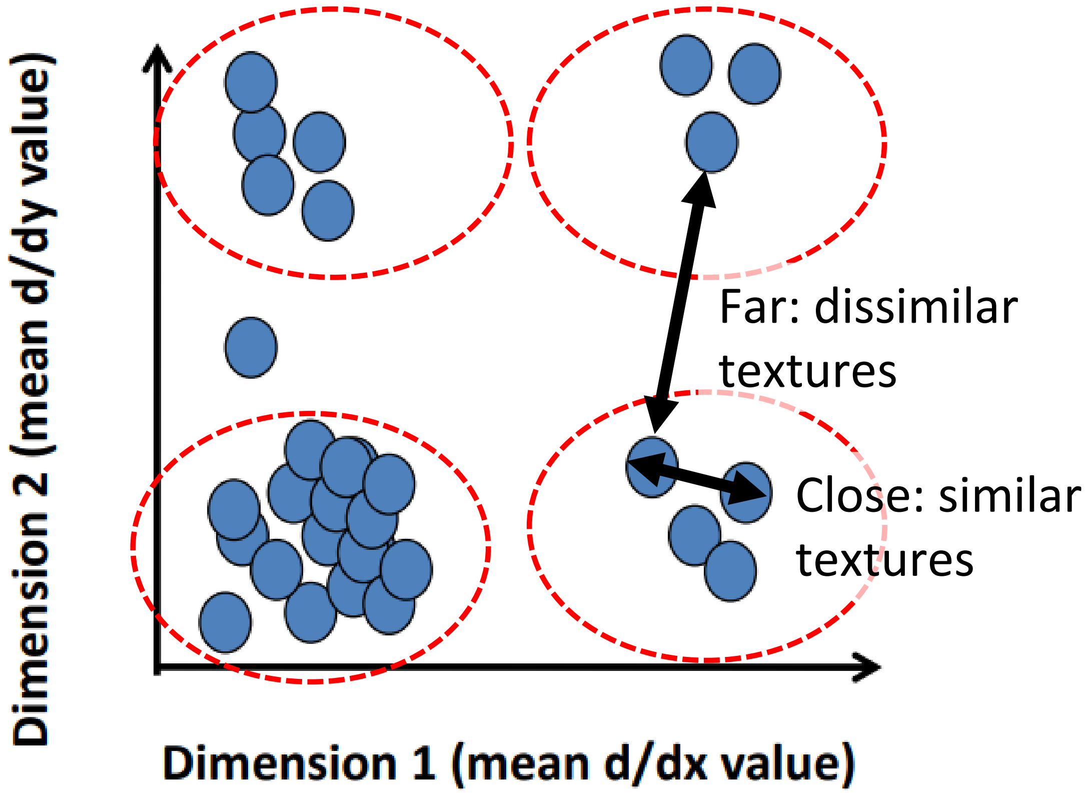
Texture Representation

Each window is now labelled with one of the four group labels

This is a better way to represent textures than using each pixel



Texture Representation



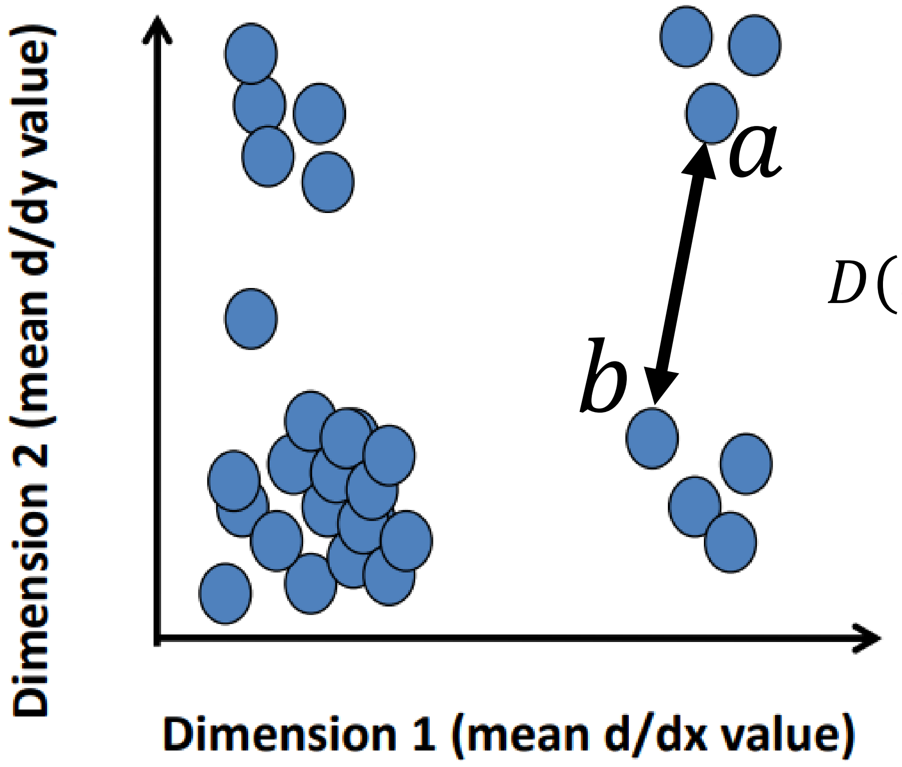
	Mean d/dx value	Mean d/dy value
Win. #1	4	10
Win. #2	18	7
⋮	⋮	⋮
Win. #9	20	20

⋮

statistics to summarize patterns in small windows

Differentiating Textures

How can we differentiate between texture windows?

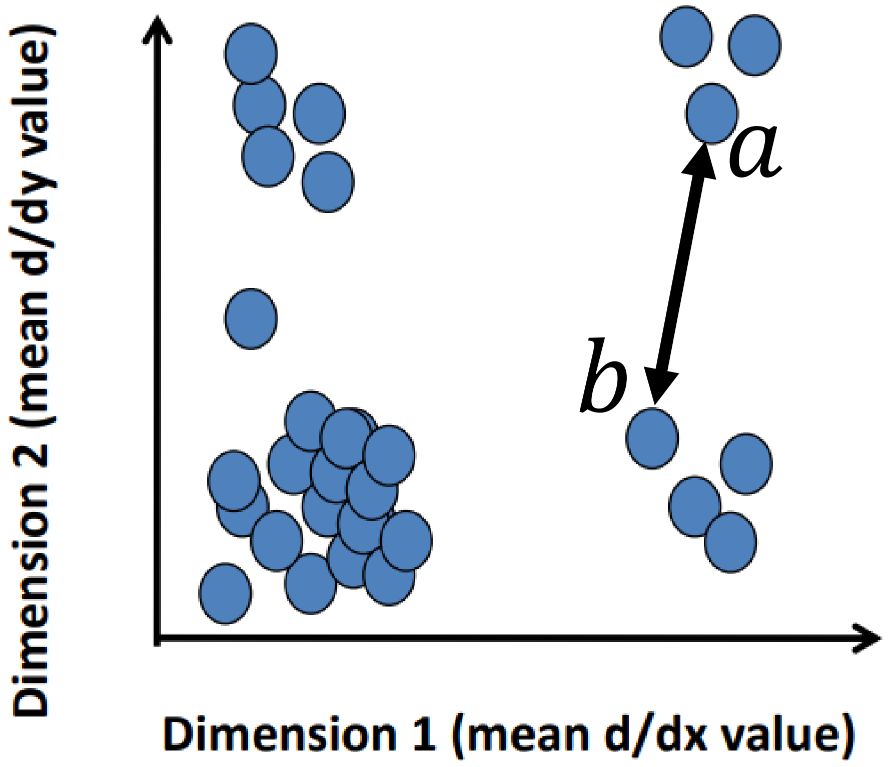


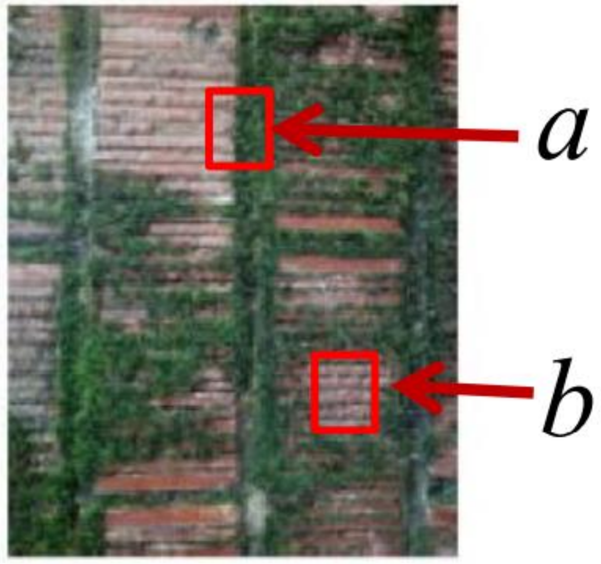
$$D(a,b) = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2}$$

Since there are only 2 dimensions, it is easy to determine the distance between the textures represented in two windows (*a* and *b* in example)

Differentiating Textures

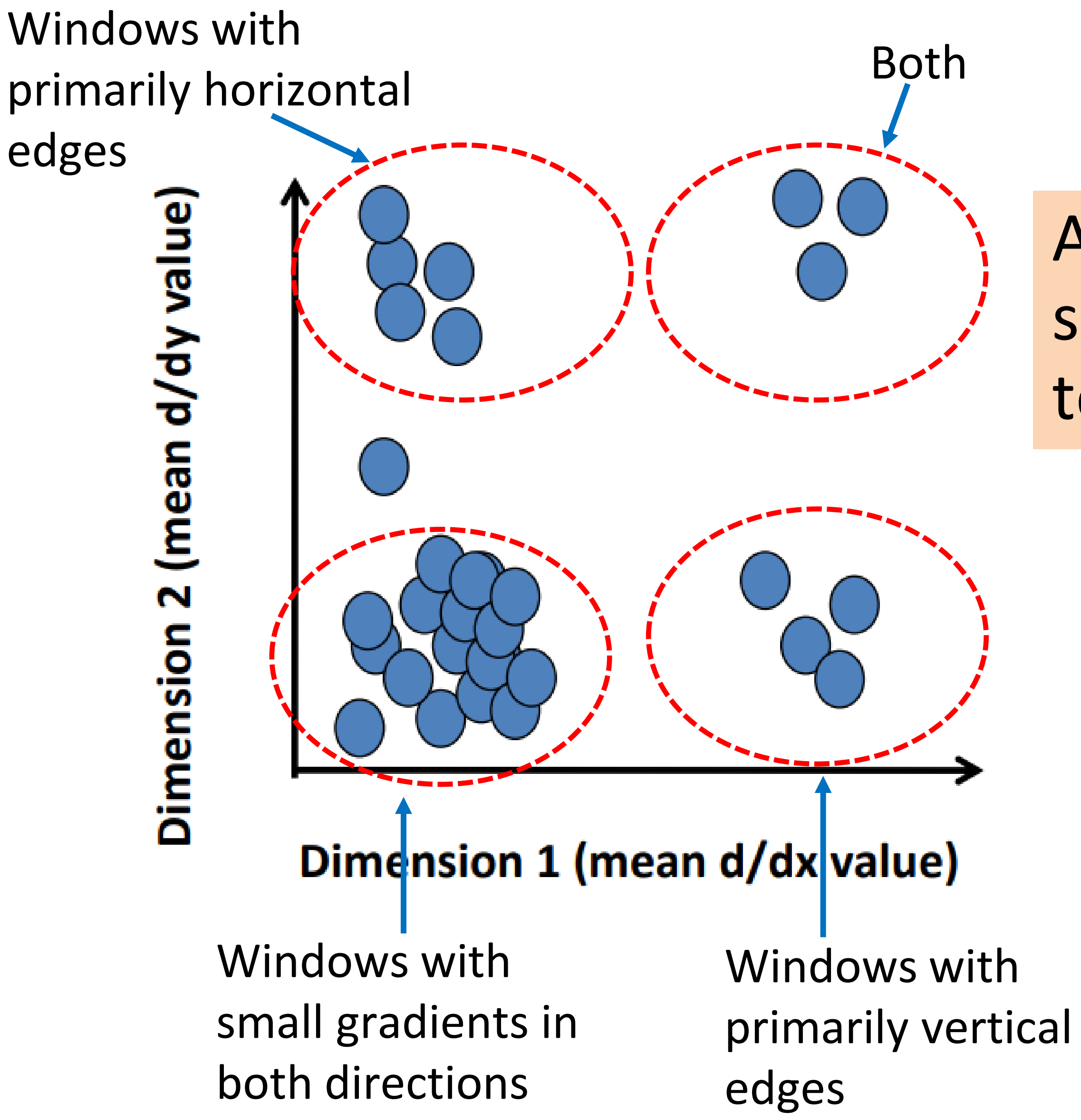
How can we differentiate between texture windows?





Distance reveals how dissimilar texture from window a is with texture from window b.

Issue #1: Texture information

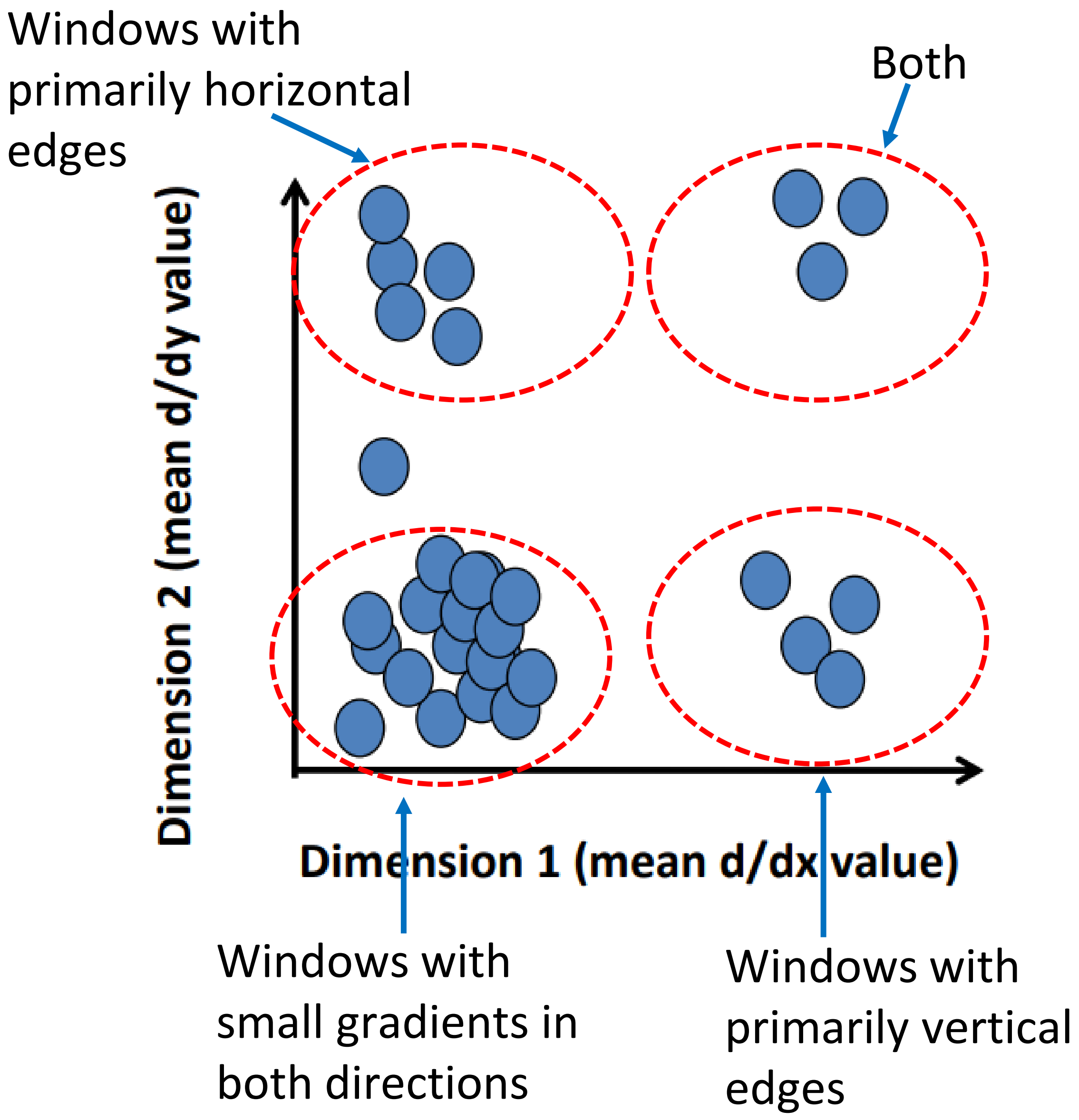

Windows with primarily horizontal edges
Both
Dimension 2 (mean d/dy value)
Dimension 1 (mean d/dx value)
Windows with small gradients in both directions
Windows with primarily vertical edges

Are 2 values (dimension = 2) sufficient to capture the texture information?

Solution:

[redacted]

Issue #2: Texture groupings


Windows with primarily horizontal edges
Both
Dimension 2 (mean d/dy value)
Dimension 1 (mean d/dx value)
Windows with small gradients in both directions
Windows with primarily vertical edges

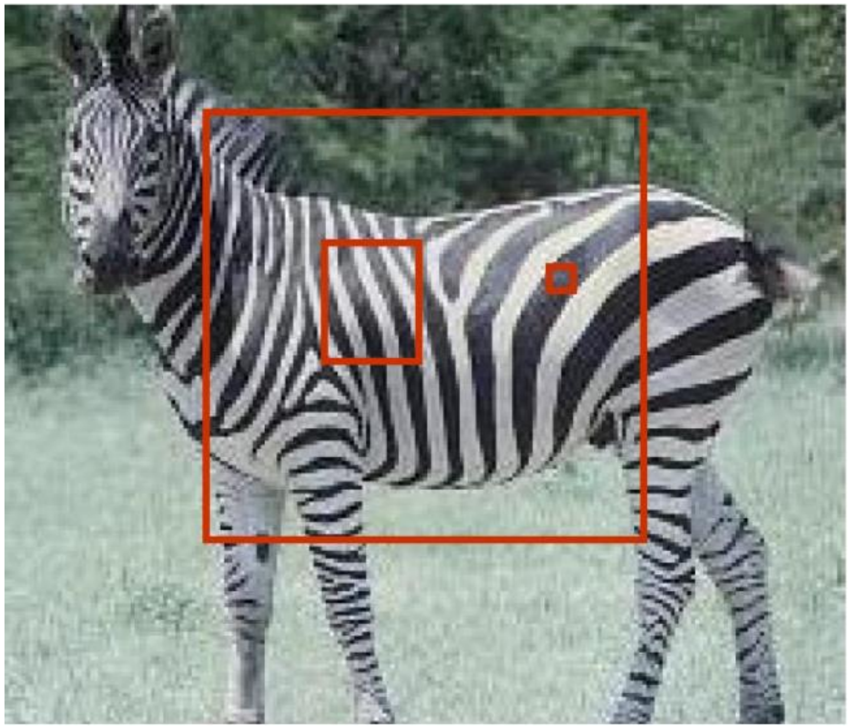
How to know the "groups" of textures and then assign them?

Solution:

[redacted]

Other Issues

- Window scale
  - We are assuming we know the relevant window size to obtain these statistics



Possible to perform scale selection by looking for window scale where <u>texture description is not changing</u>

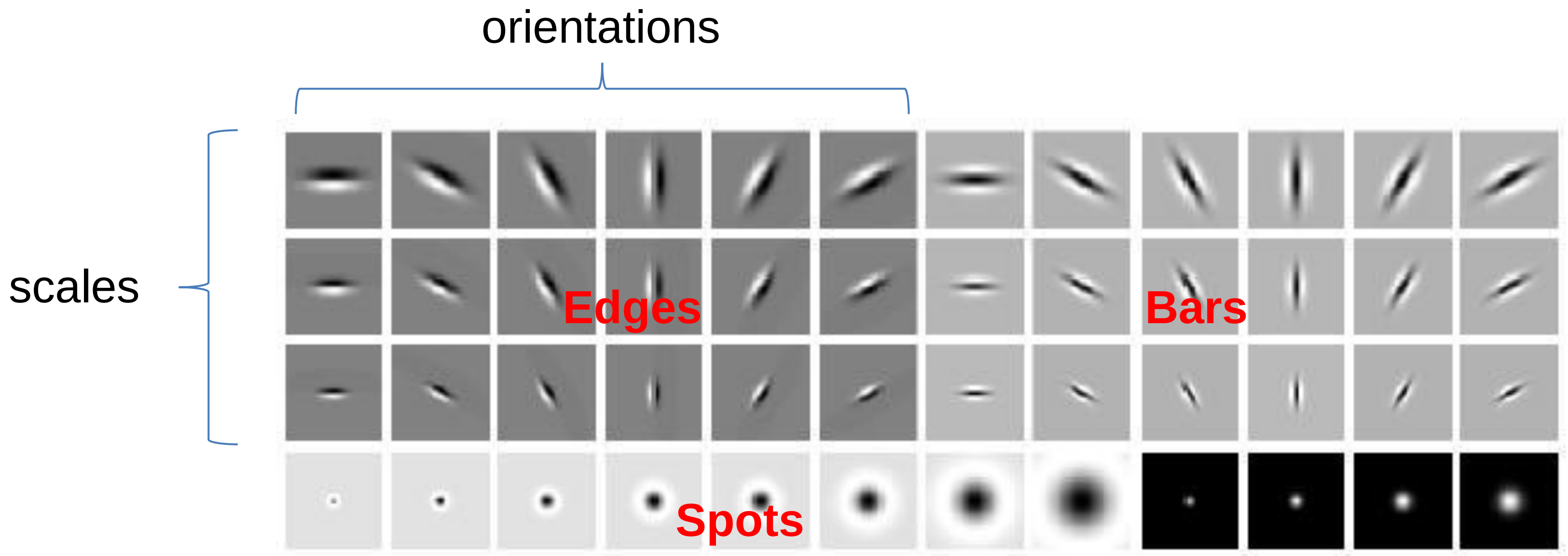
Resolving issue #1

Are **TWO** types of filters sufficient for describing texture in an image?

Filter bank

- Our previous example used only 2 filters
  - x and y derivatives revealed some information about local structure
- We can generalize to apply **a collection of multiple *(d)* filters** – also known as a "**filter bank**"
  - Feature vectors will be *d*-dimensional
  - Same way to calculate distance/dissimilarity

Filter bank

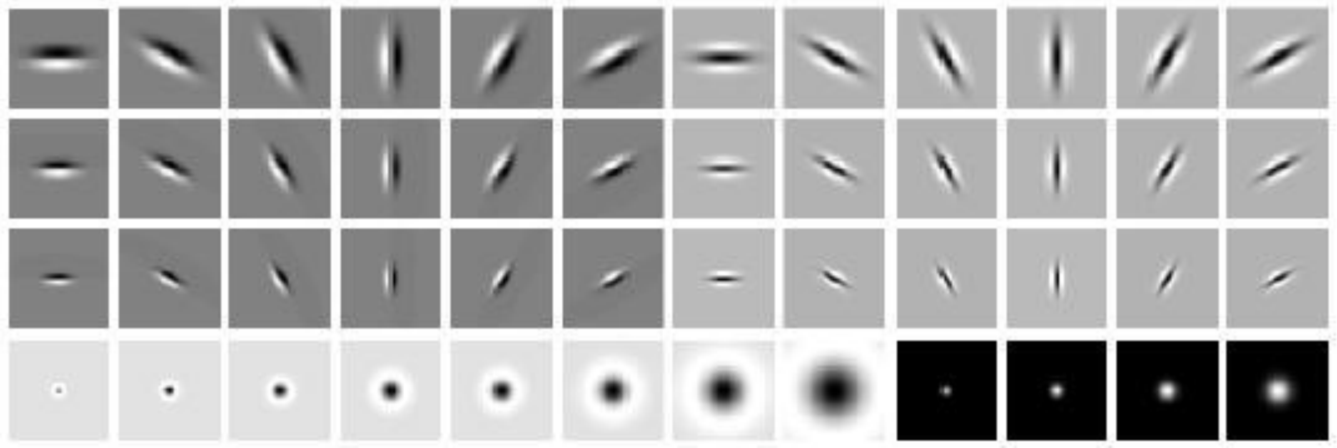


- What filters to put in the bank?
  - Typically, we want a combination of scales and orientations, and different types of patterns

Matlab code: http://www.robots.ox.ac.uk/~vgg/research/texclass/filters.html

Python code: http://www.rsgislib.org/rsgislib_imagefilter.html#filter-banks

Leung-Malik (LM) filter bank

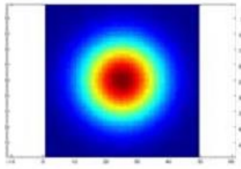


– 48 filters:

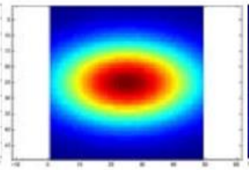
- 1st and 2nd derivative of Gaussians at 6 orientations and 3 scales (total 36)
- 8 LoG filters, 4 Gaussian filters (total 12)

Filter bank: Example

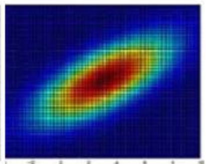
$$p(x;\mu,\Sigma)=\frac{1}{(2\pi)^{n/2}|\Sigma|^{1/2}}\exp\left(-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)\right)$$



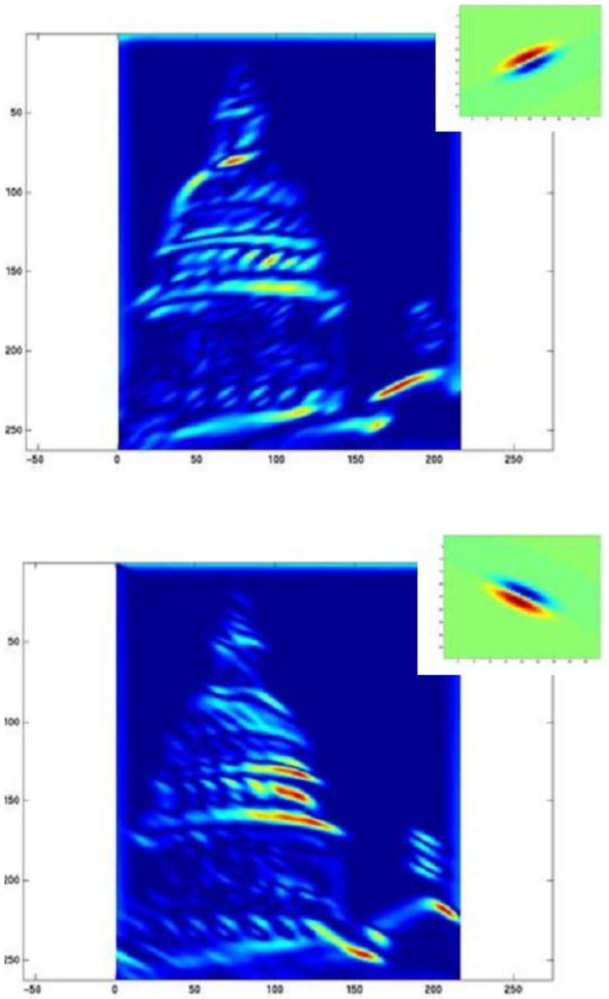
$$\Sigma=\begin{bmatrix}9 & 0\\ 0 & 9\end{bmatrix}$$

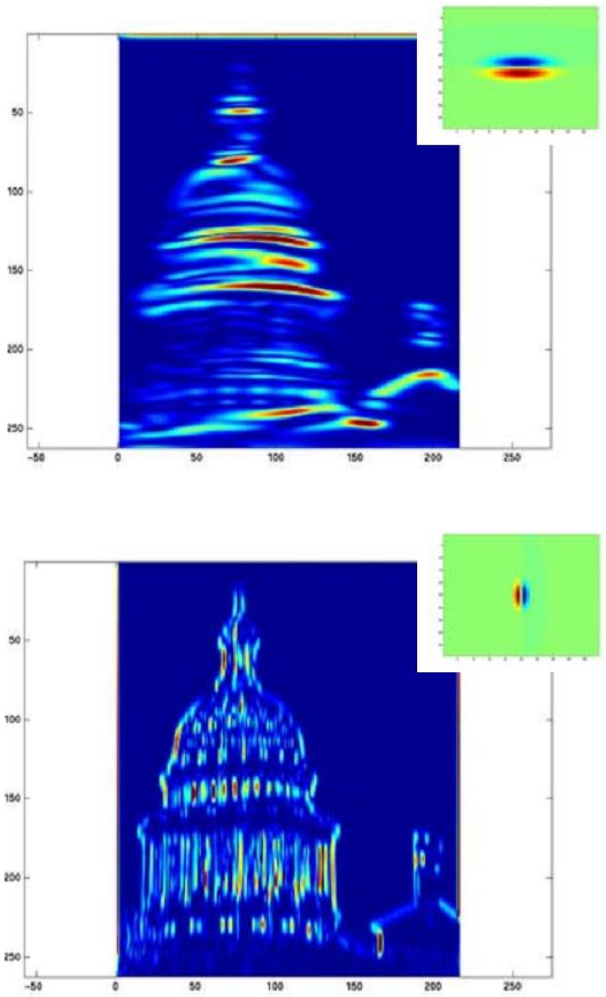


$$\Sigma=\begin{bmatrix}16 & 0\\ 0 & 9\end{bmatrix}$$



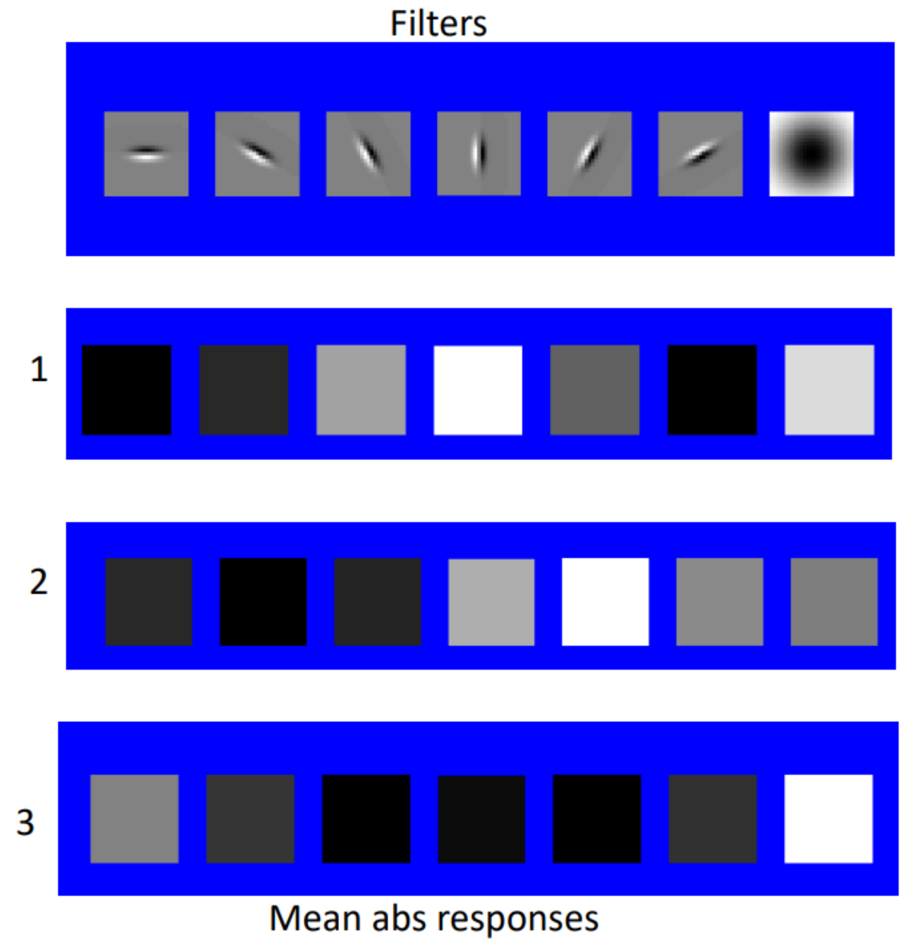
$$\Sigma=\begin{bmatrix}10 & 5\\ 5 & 5\end{bmatrix}$$

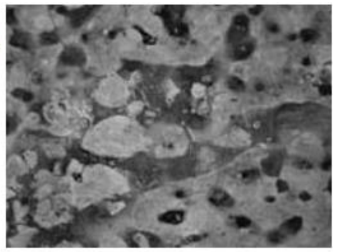


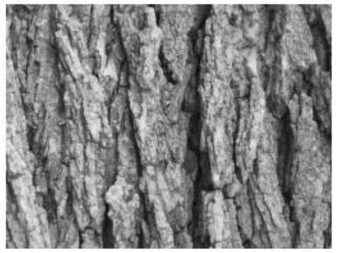


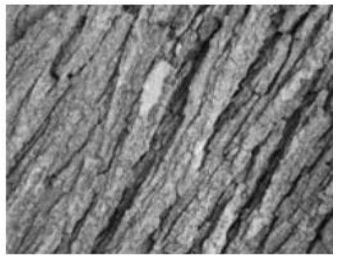
Filter bank responses

- You try: Can you match the texture to the response:

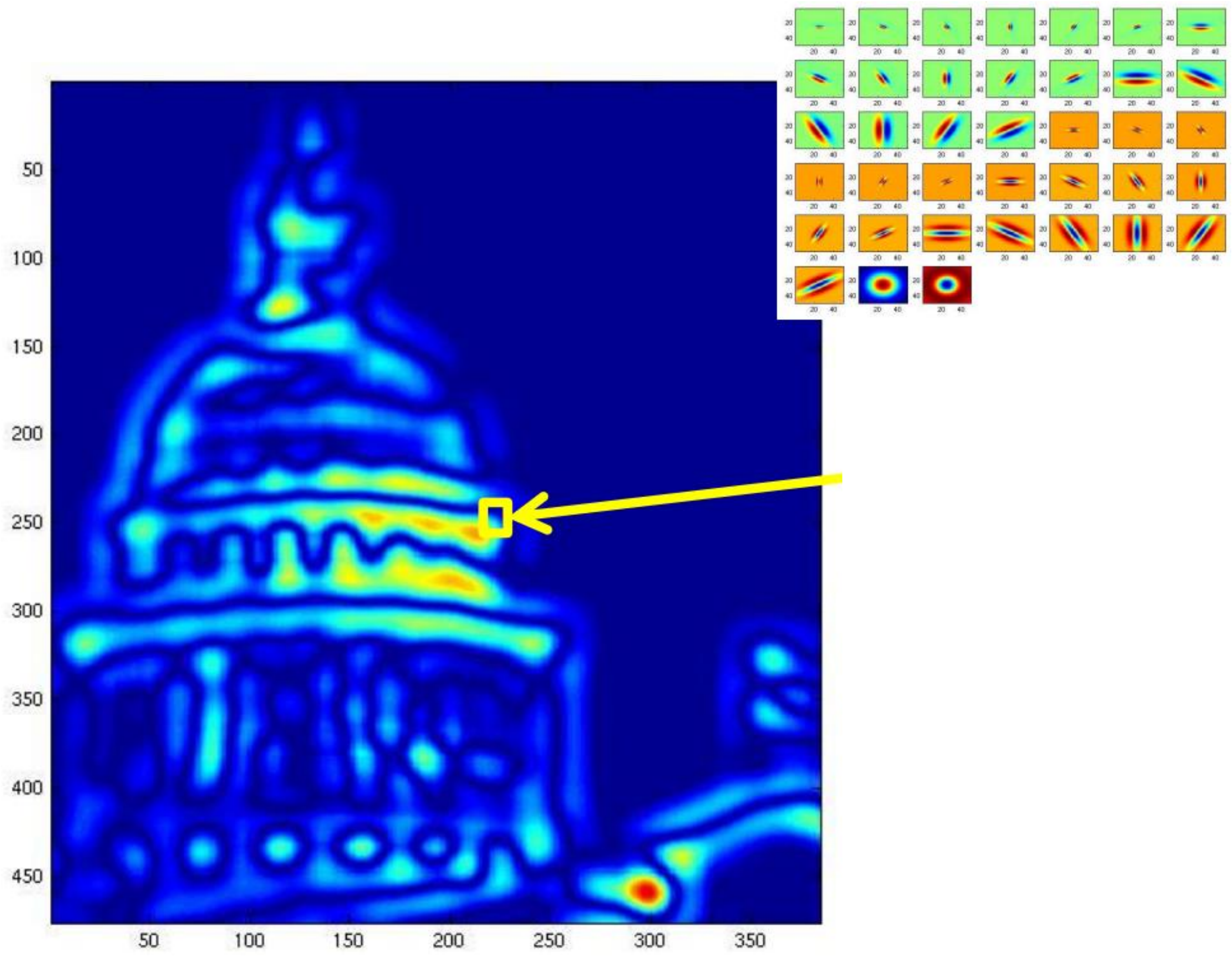


A


B


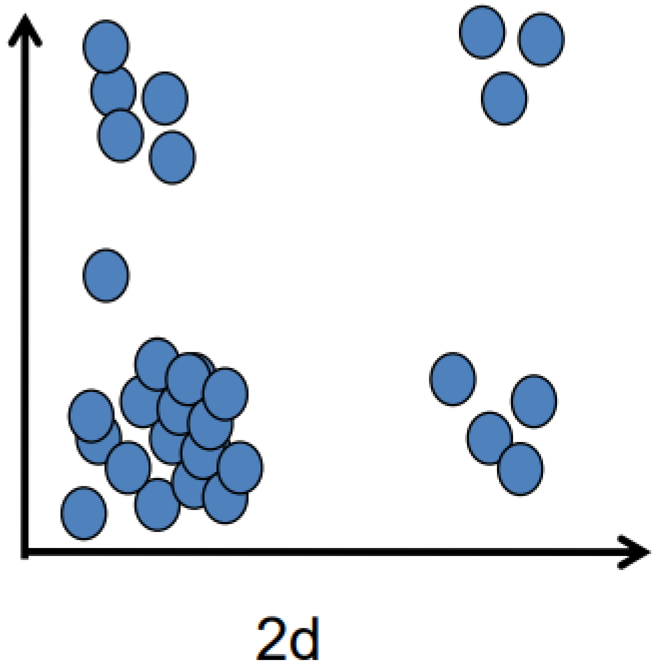
C


Filter bank responses ⇒ Feature



d-dimensional features

- Previously: 2 filters ⇒ 2-dimensional feature vector
- Now: 48 filters ⇒ 48-dimensional feature vectors
- Distance can be measured with L2-distance or Euclidean distance



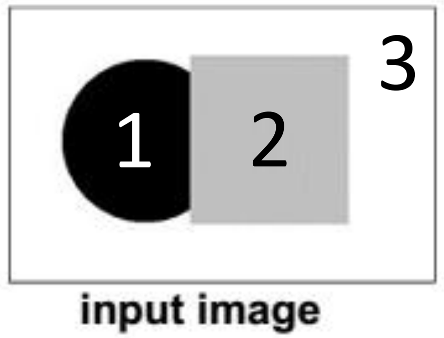
$$D(a,b) = \sqrt{\sum_{i=1}^{d}(a_i - b_i)^2}$$

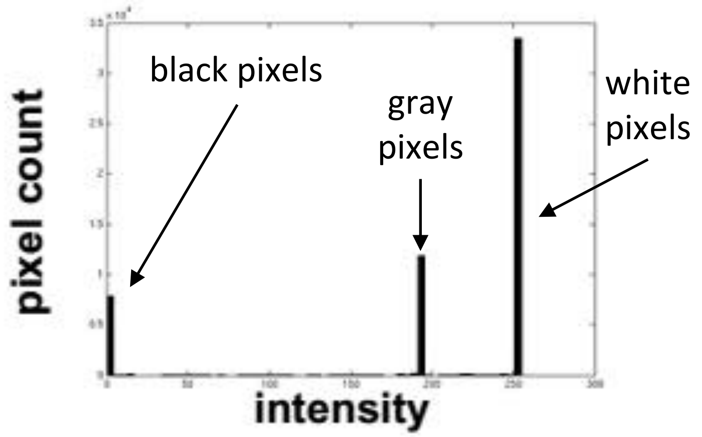
Euclidean distance (L_2)

Resolving issue #2

How do we group these texture information into "groups"?

Motivation



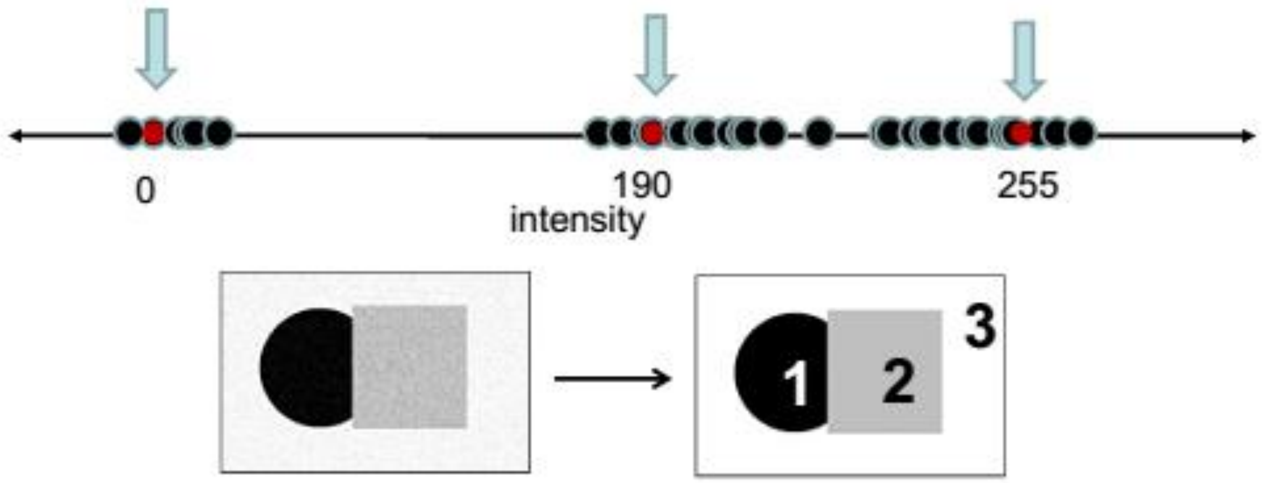


Threshold to 3 regions. Easy.

Now, how to determine the "three" main intensities that define the groups seen in the image?

One way is to cluster.

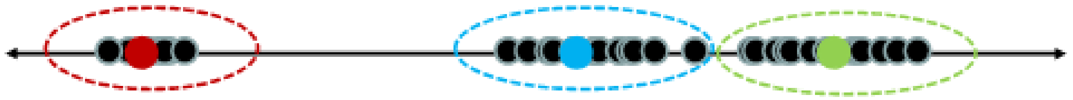
Finding Clusters



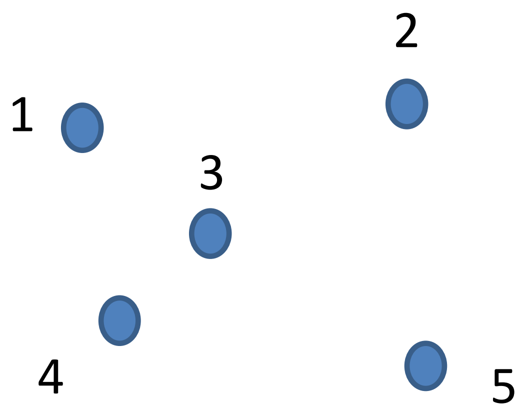
- **Aim**: Choose three "centres" as the representative intensities, and label every pixel according to which of these centres it is nearest to
- Best cluster centres are those that minimize sum of squared distances (SSD) between all points and their nearest cluster centre

$$\sum_{\text{clusters } i} \sum_{\text{points p in cluster } i} ||p - c_i||^2$$

The intuition behind SSD



SSD $\sum_{\text{clusters } i} \sum_{\text{points p in cluster } i} \|p - c_i\|^2$

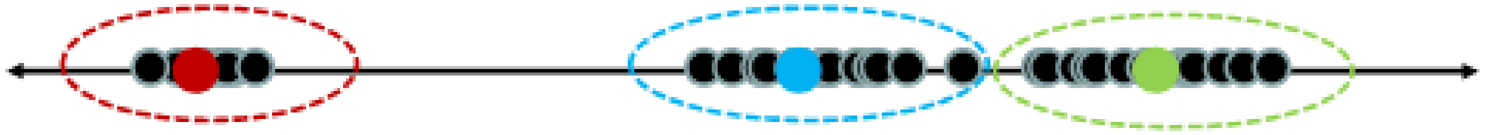


Look at this cluster of points. Which of these points will be the **NEAREST** to all other points?

How would you find the answer?

How to solve this?

- "Chicken and egg" problem!



  - **If we knew the cluster centres**, we could allocate points to groups by assigning each to its closest centre
  - **If we knew the group memberships**, we could get the centres by computing the mean per group

K-means clustering

- **Goal**: Cluster to minimize variance in data given clusters

$$c^*,\ \delta^* = \underset{c,\delta}{\arg\min}\, \frac{1}{N}\sum_{j}^{N}\sum_{i}^{K} \underset{\text{Whether } x_j \text{ is assigned to } c_i}{\delta_{ij}} \left(\overset{\text{Cluster center}}{c_i} - \overset{\text{Data}}{x_j}\right)^2$$

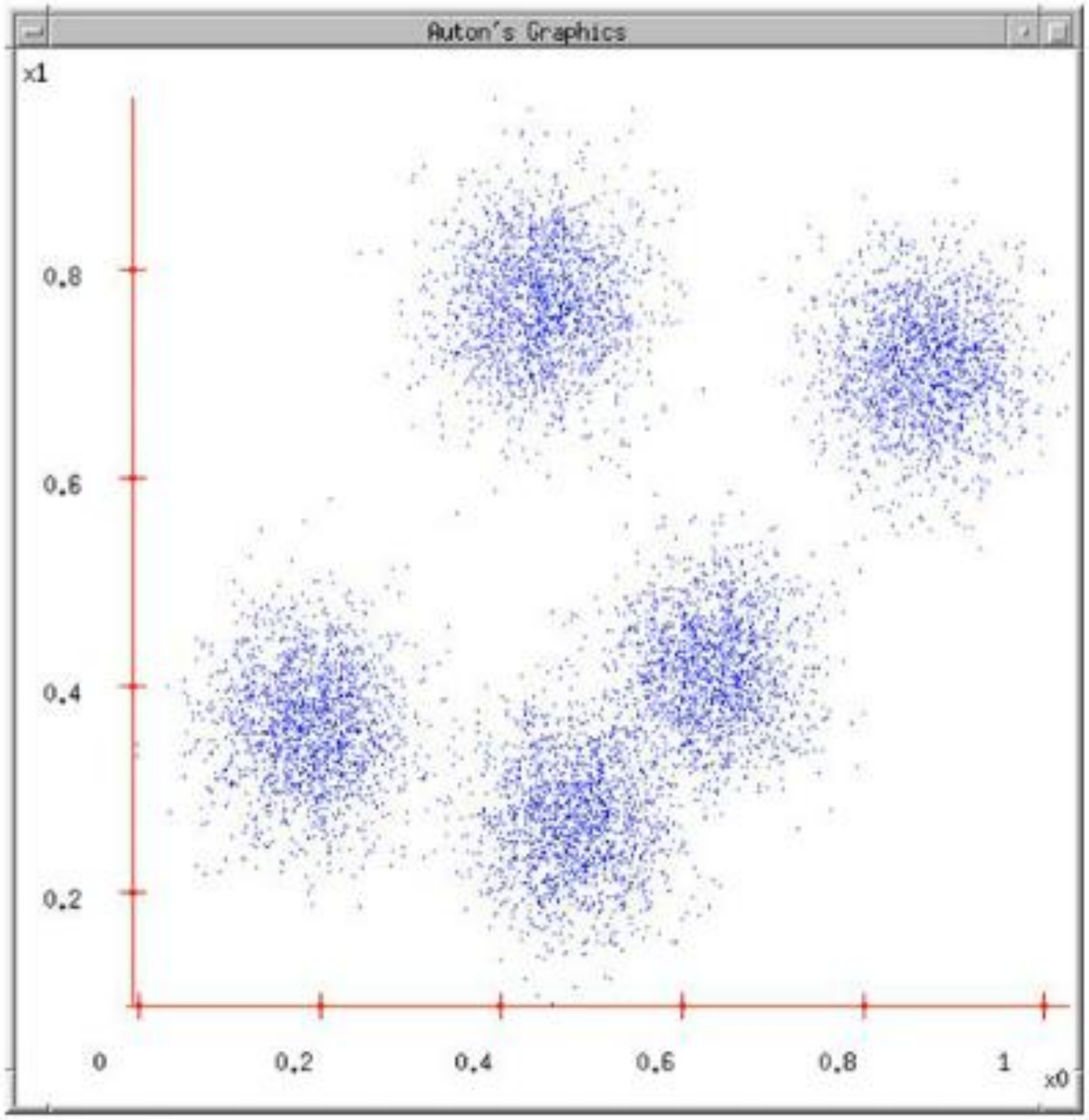
K-means clustering

- Basic idea: Randomly initialize the *k* cluster centres, and iterate between the two steps we just saw.
  1. Randomly initialize cluster centres $c_1, \ldots c_k$
  2. Given cluster centres, determine points in each cluster – for each point *p*, find closest c_i, put *p* into cluster *I*
  3. Given points in each cluster, solve for c_i – set c_i to the mean of points in cluster *I*
  4. If c_i have changed, repeat Step 2. Otherwise, terminate.
- Properties:
  – Will always converge to *some* solution
  – Does not always find the global minimum of objective function

$$\sum_{\text{clusters } i} \quad \sum_{\text{points p in cluster } i} \|p - c_i\|^2$$

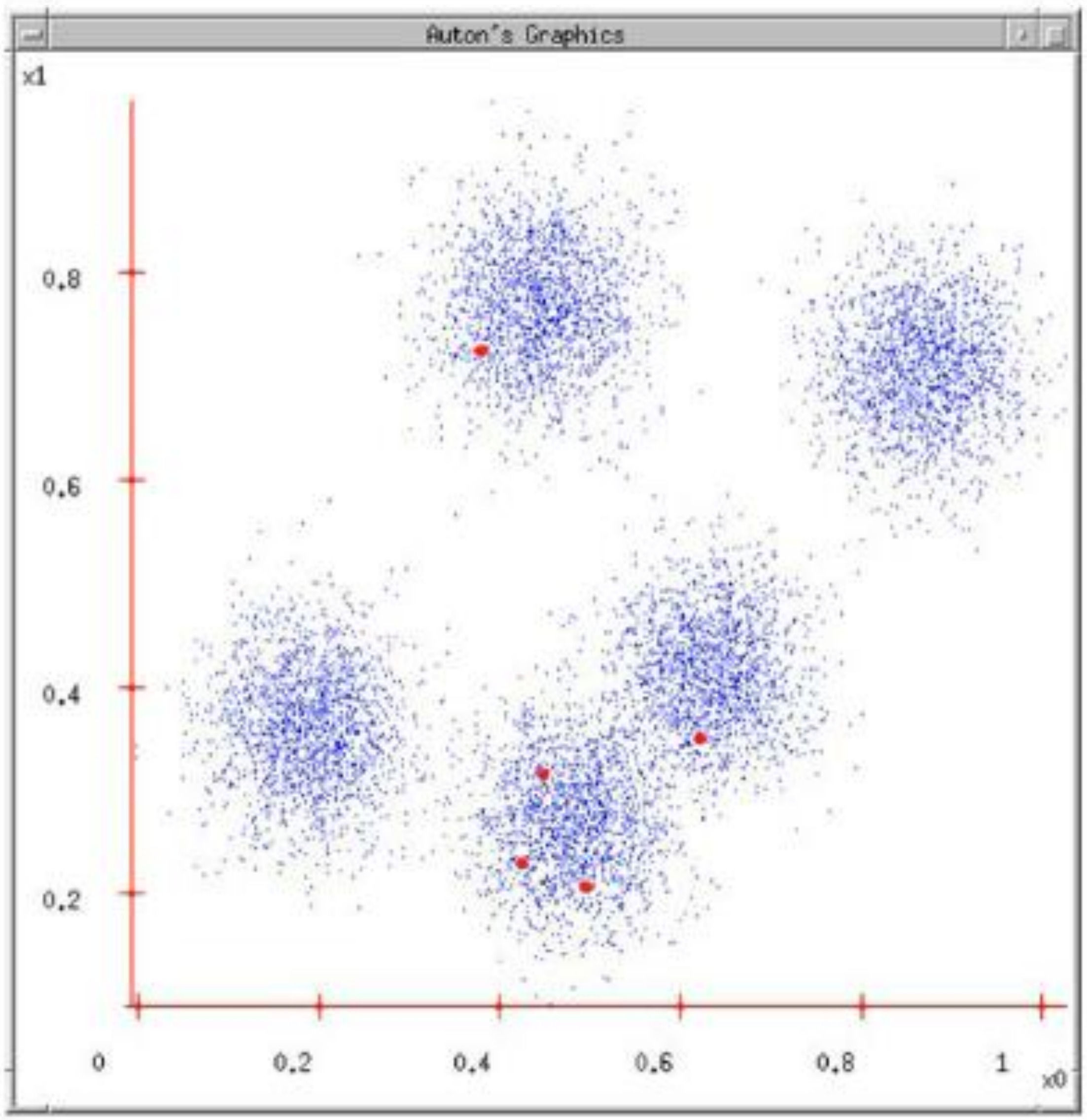
K-means clustering

1. Determine beforehand how many clusters or value of *k*



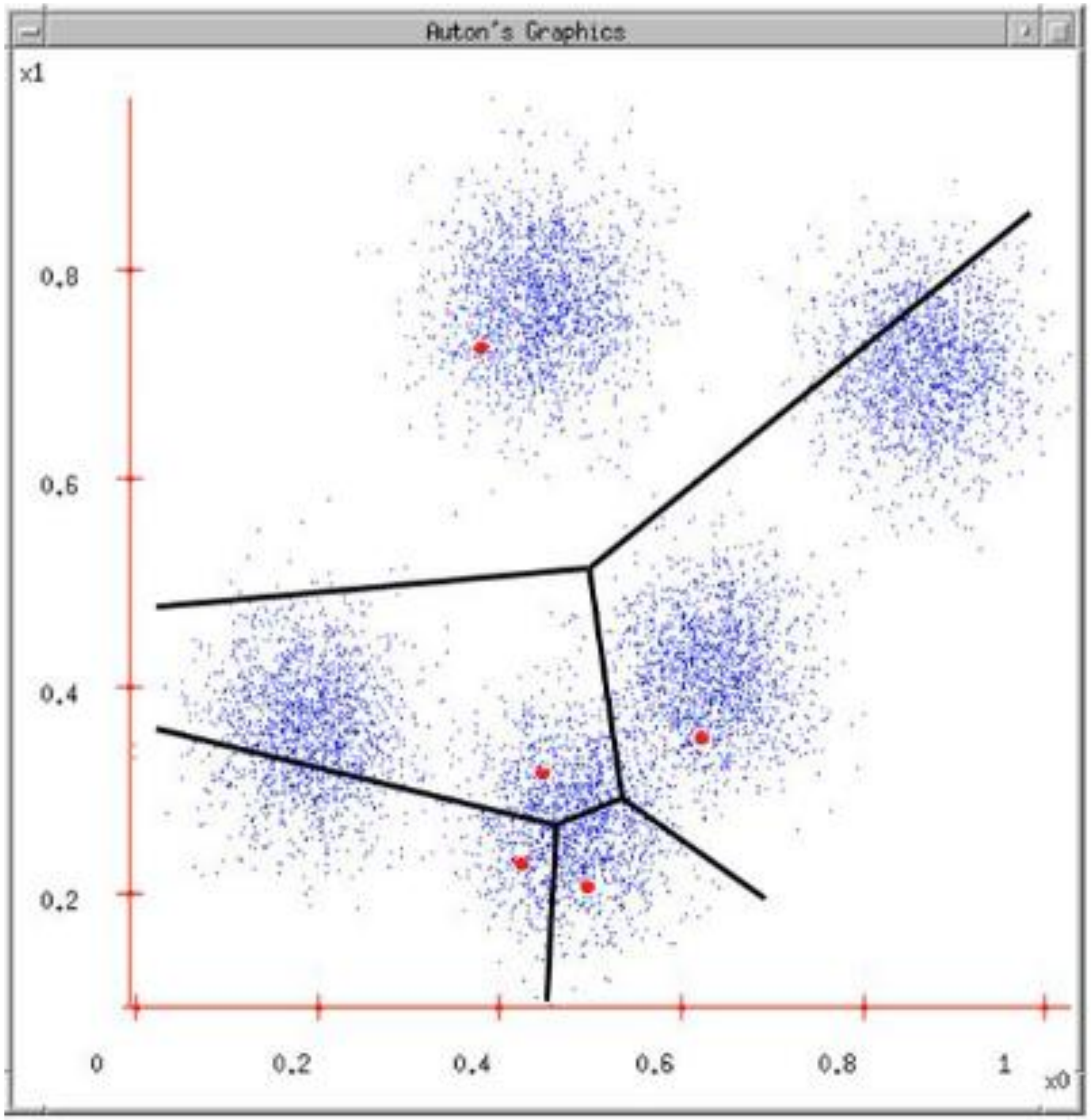
K-means clustering

1. Determine beforehand how many clusters or value of *k*
2. Randomly guess *k* cluster centre locations



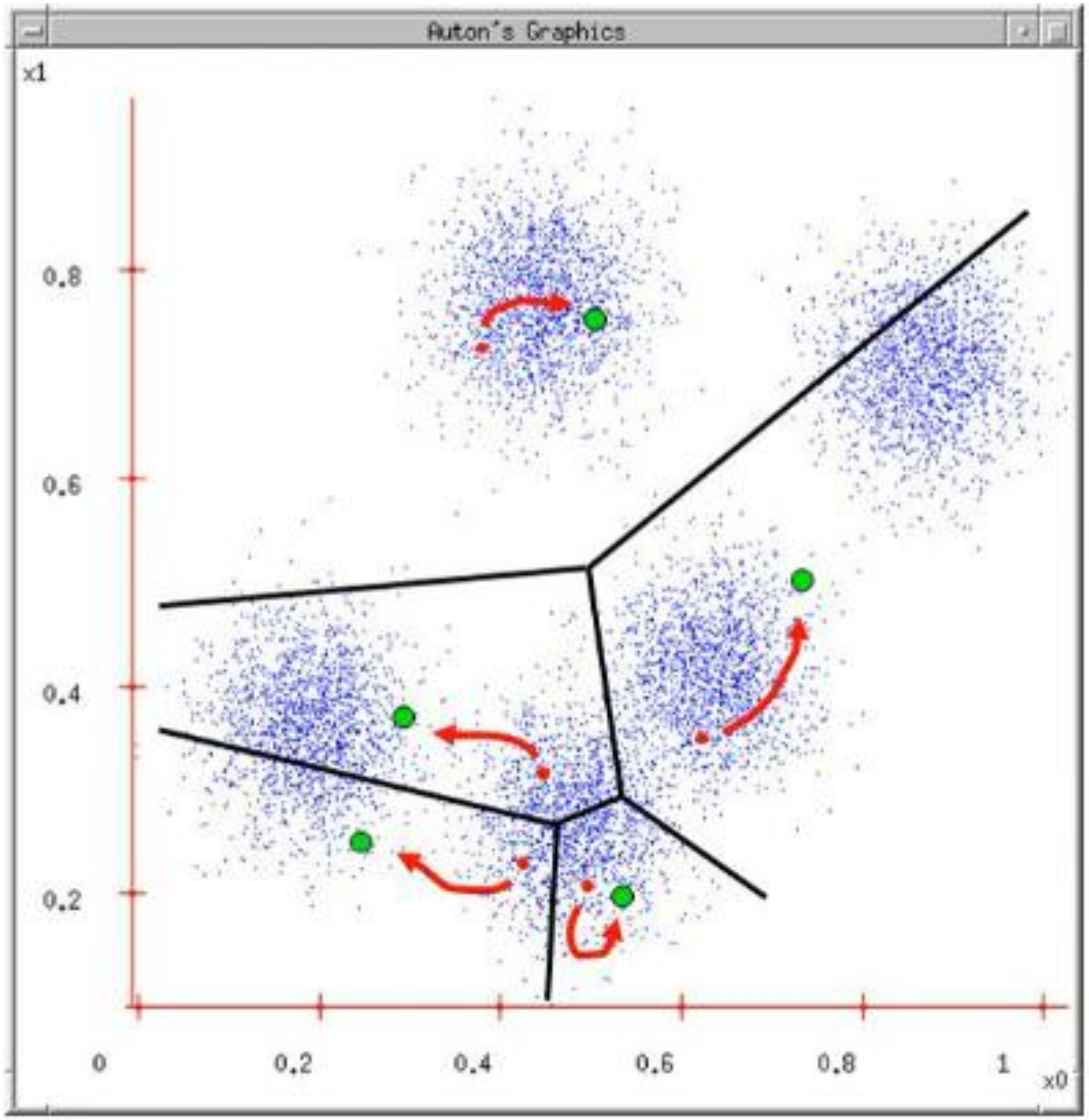
K-means clustering

1. Determine beforehand how many clusters or value of *k*
2. Randomly guess *k* cluster centre locations
3. Each data point finds out which centre it is closest to (each centre “owns” a set of points)



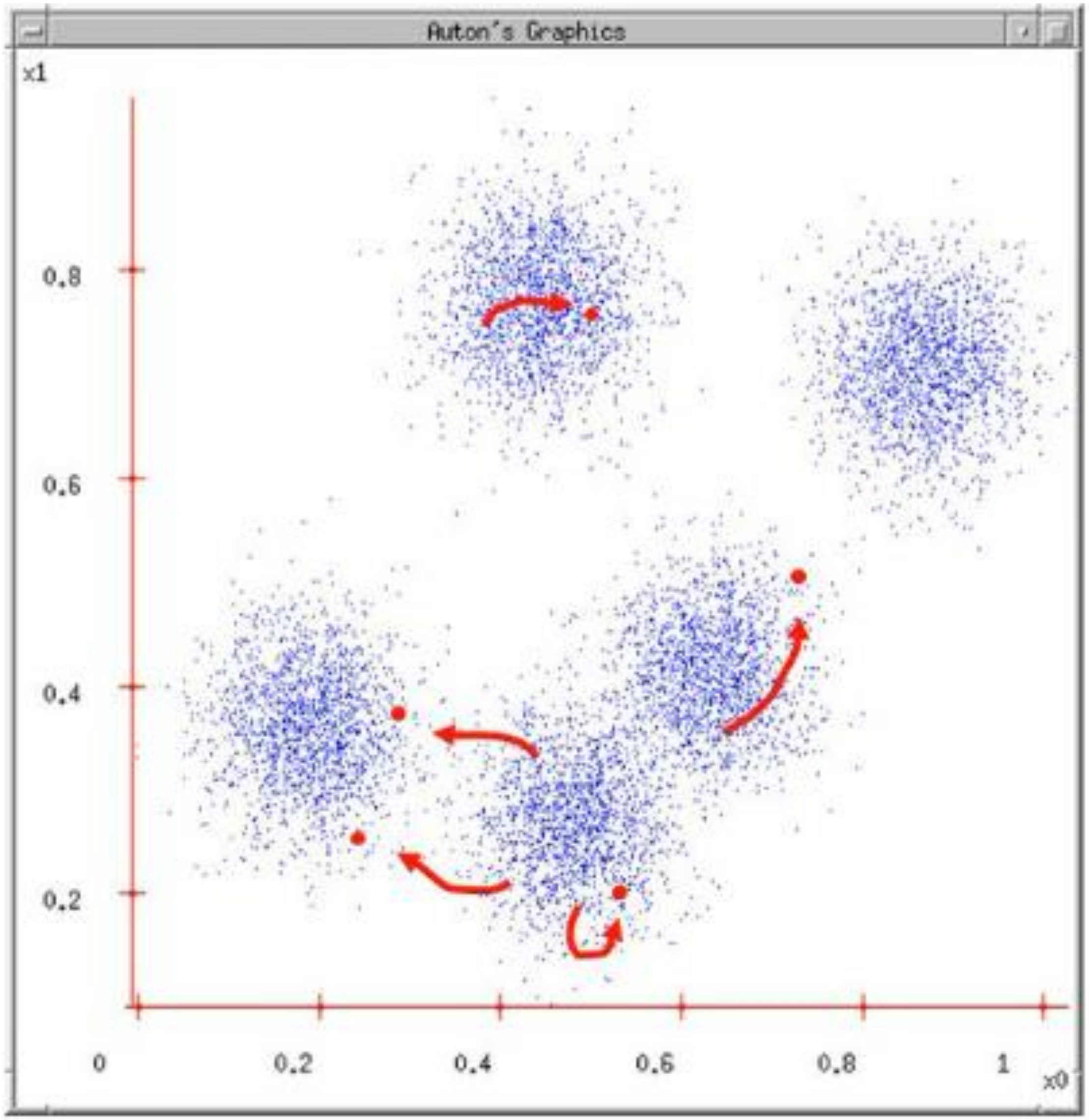
K-means clustering

1. Determine beforehand how many clusters or value of *k*
2. Randomly guess *k* cluster centre locations
3. Each data point finds out which centre it is closest to
4. Each centre finds the centroid of its own group



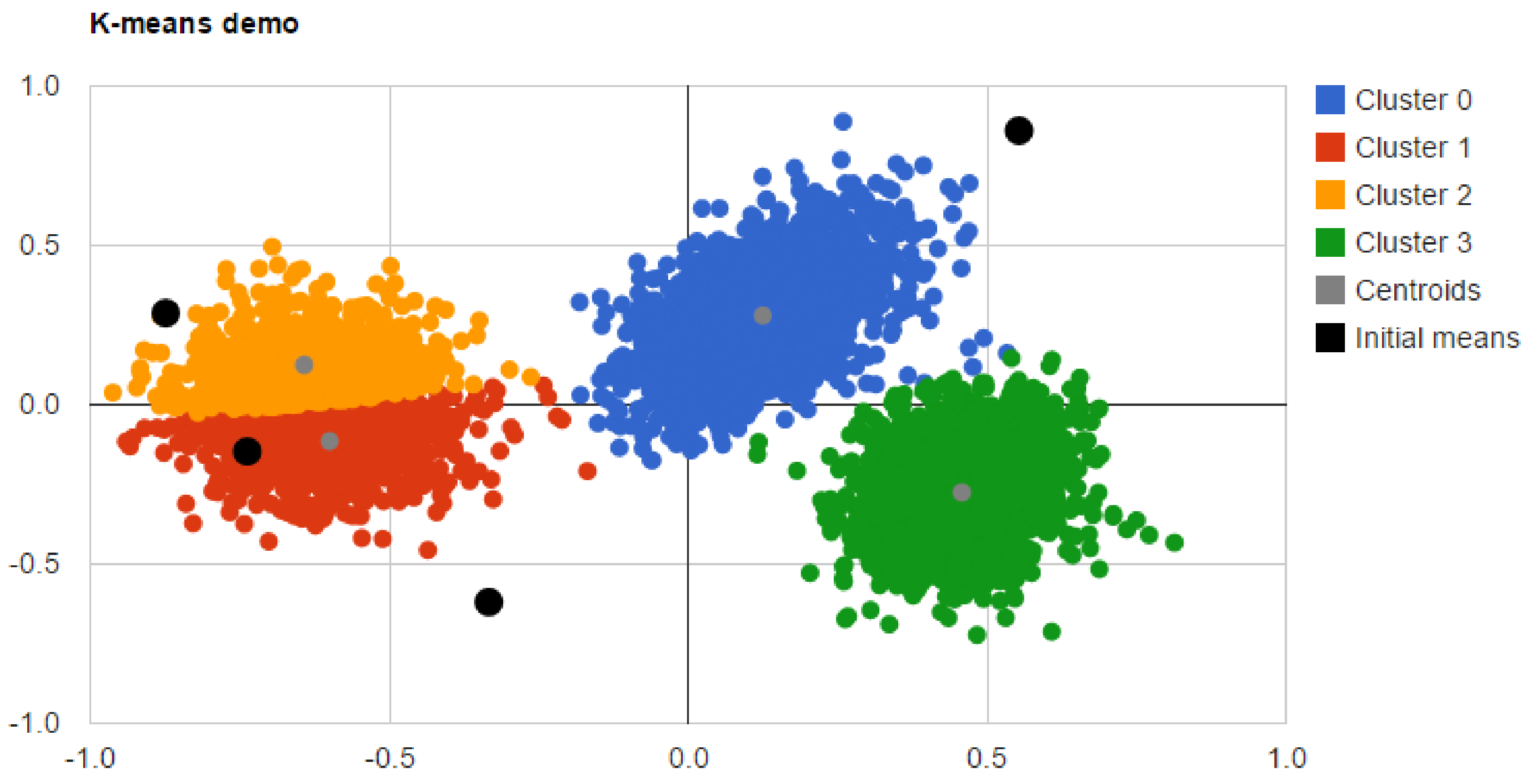
K-means clustering

1. Determine beforehand how many clusters or value of *k*
2. Randomly guess *k* cluster centre locations
3. Each data point finds out which centre it is closest to
4. Each centre finds the centroid of its own group
5. With the new centroid, repeat again the process from (3) until algorithm terminates



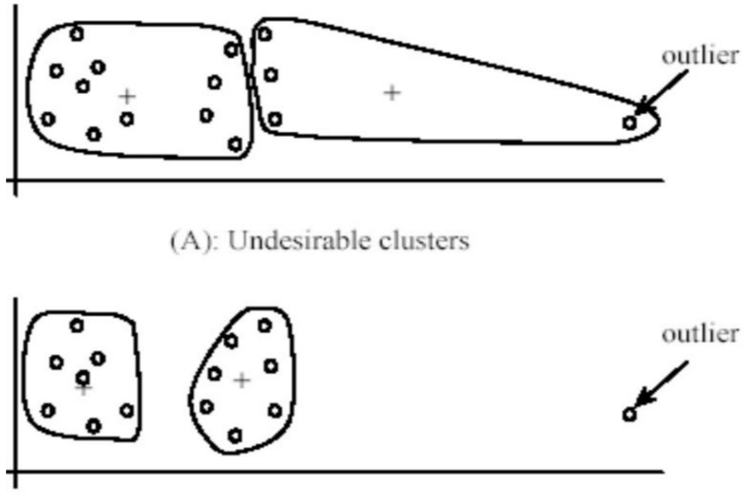
K-means clustering

- A nice demo: http://syskall.com/kmeans.js/



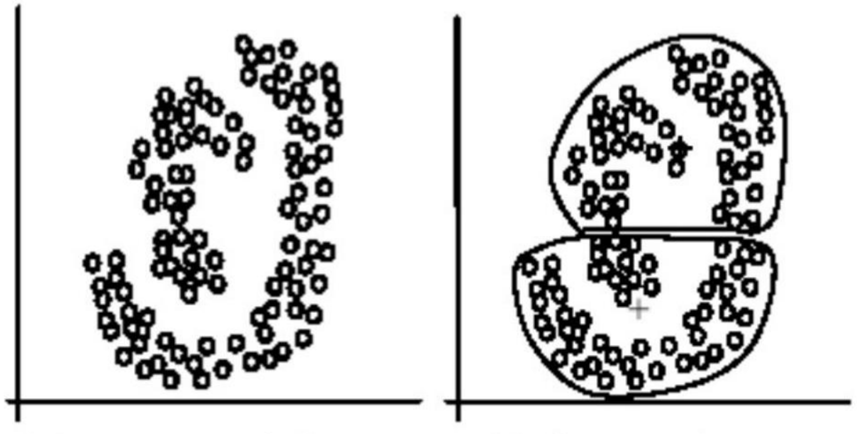
K-means: Pros and Cons

- **Pros**
  - Simple, fast to compute
  - Converges to local minimum of within-cluster squared error
- **Cons**
  - Setting k?
  - Sensitive to initial centres
  - Sensitive to outliers
  - Detects spherical clusters
  - Assuming means can be computed



(A): Undesirable clusters

(B): Ideal clusters



(A): Two natural clusters (B): *k*-means clusters

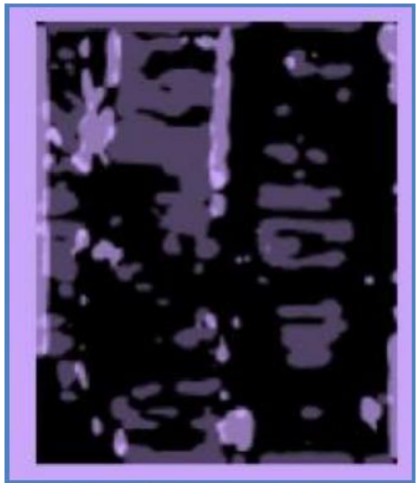
Histograms for Texture Representation

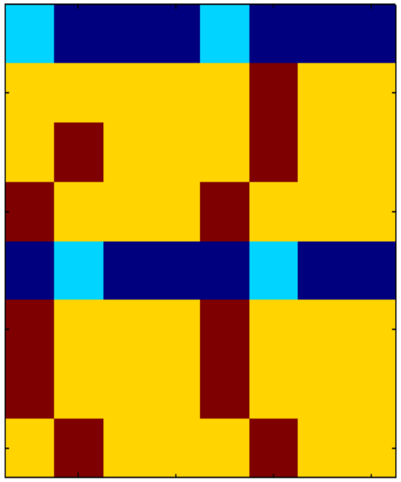
Texture Representation Revisited

- Textures are made up of **repeated local patterns**, so
  - **Describe** their **statistics** within each local window (or “neighbourhood” so to speak)
    - Mean, standard deviation
    - **(and at a higher level..) Histogram of feature occurrences**

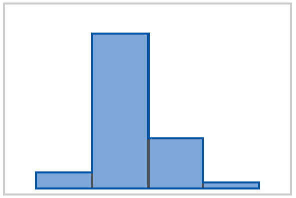
Example Revisited

original image


visualization of the assignment to texture "types"



Instead of only assigning each pixel to texture types, build some **statistics** about it after that

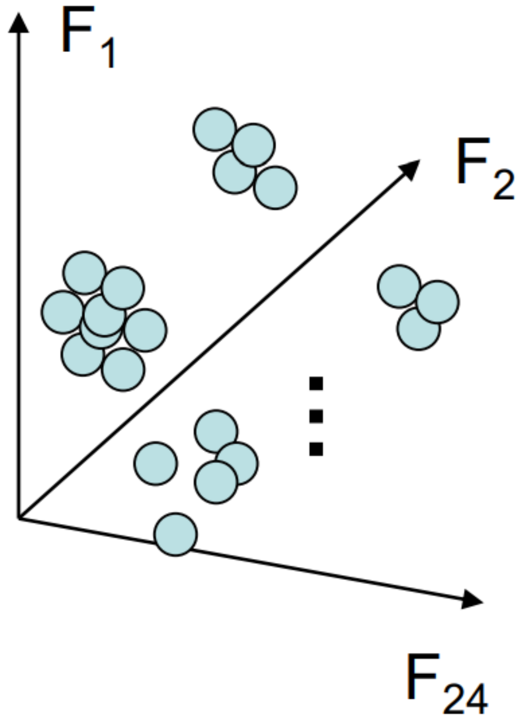


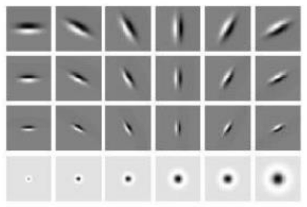
Histogram of feature occurrences

Based on the earlier e.g. a histogram of 4 bins is now the new "feature vector"
⇒ Describes the statistical distribution of textures in an image

Texture-based grouping

- Grouping pixels based on **texture** similarity



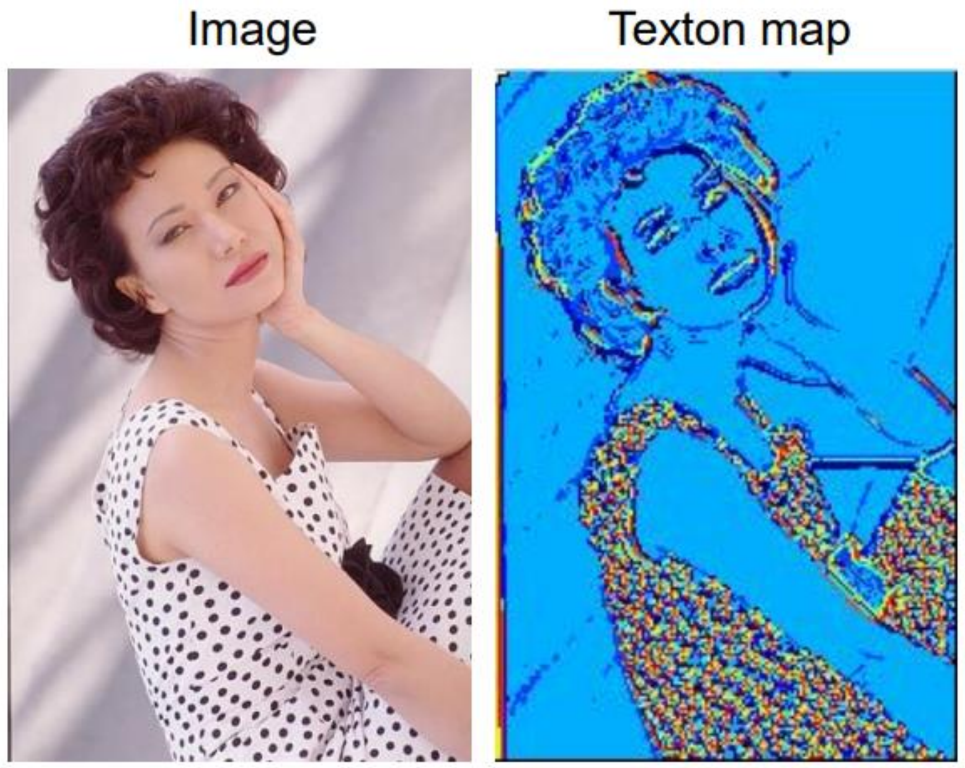


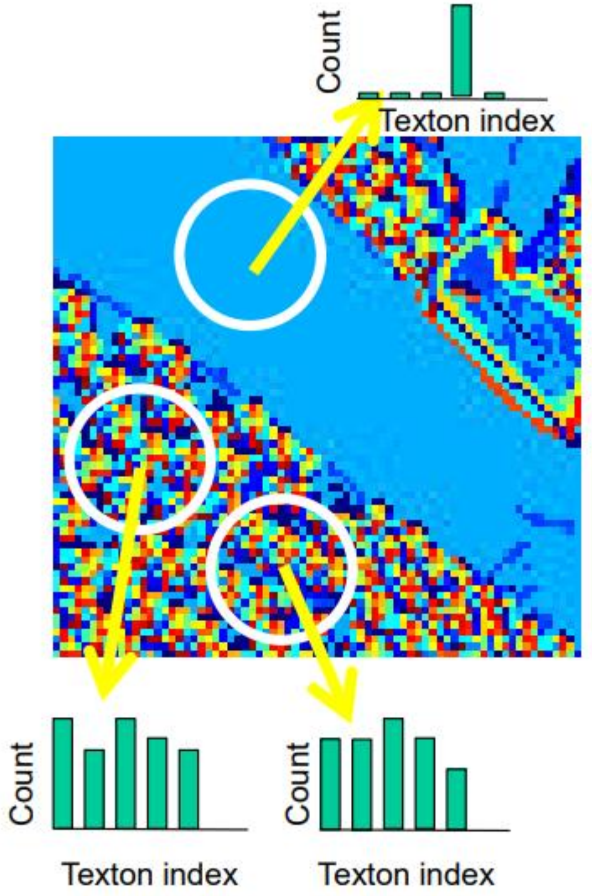
Filter bank of 24 filters

- Feature space: Filter bank responses (e.g. 24-D)

"Textons"

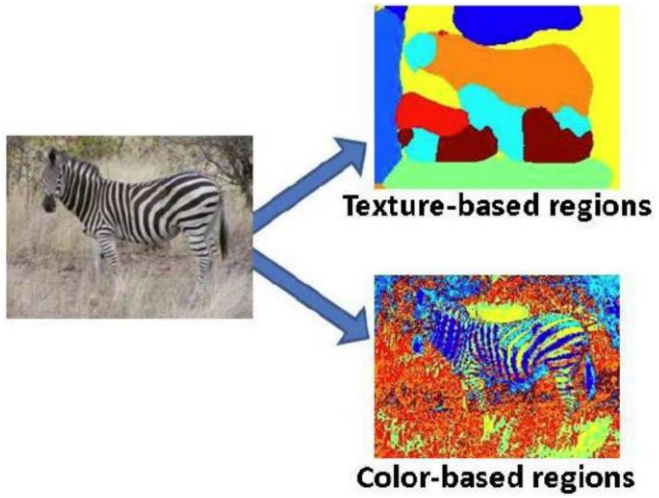
- Find "textons" by **clustering** vectors of filter bank outputs
- Describe texture in a window based on **texton histogram**

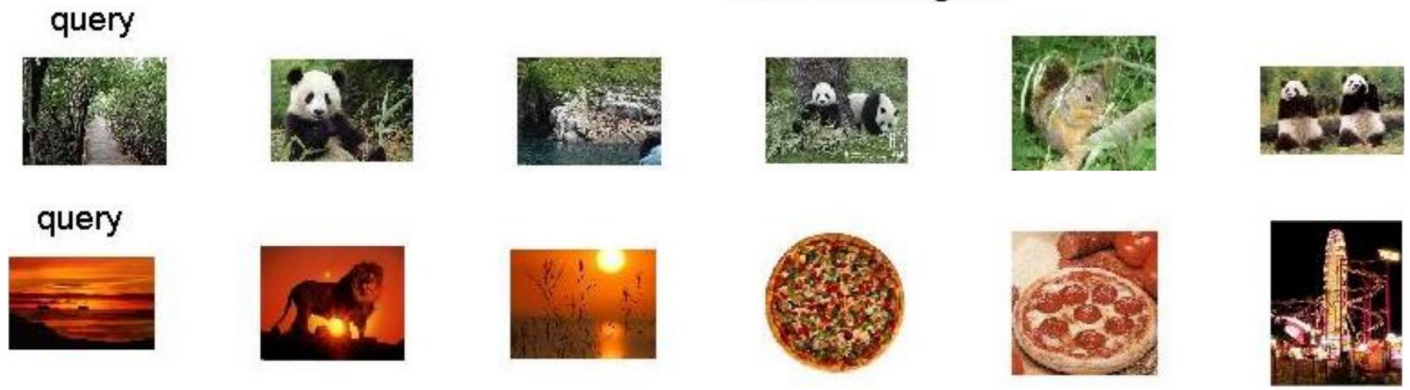




Adapted from Lana Lazebnik

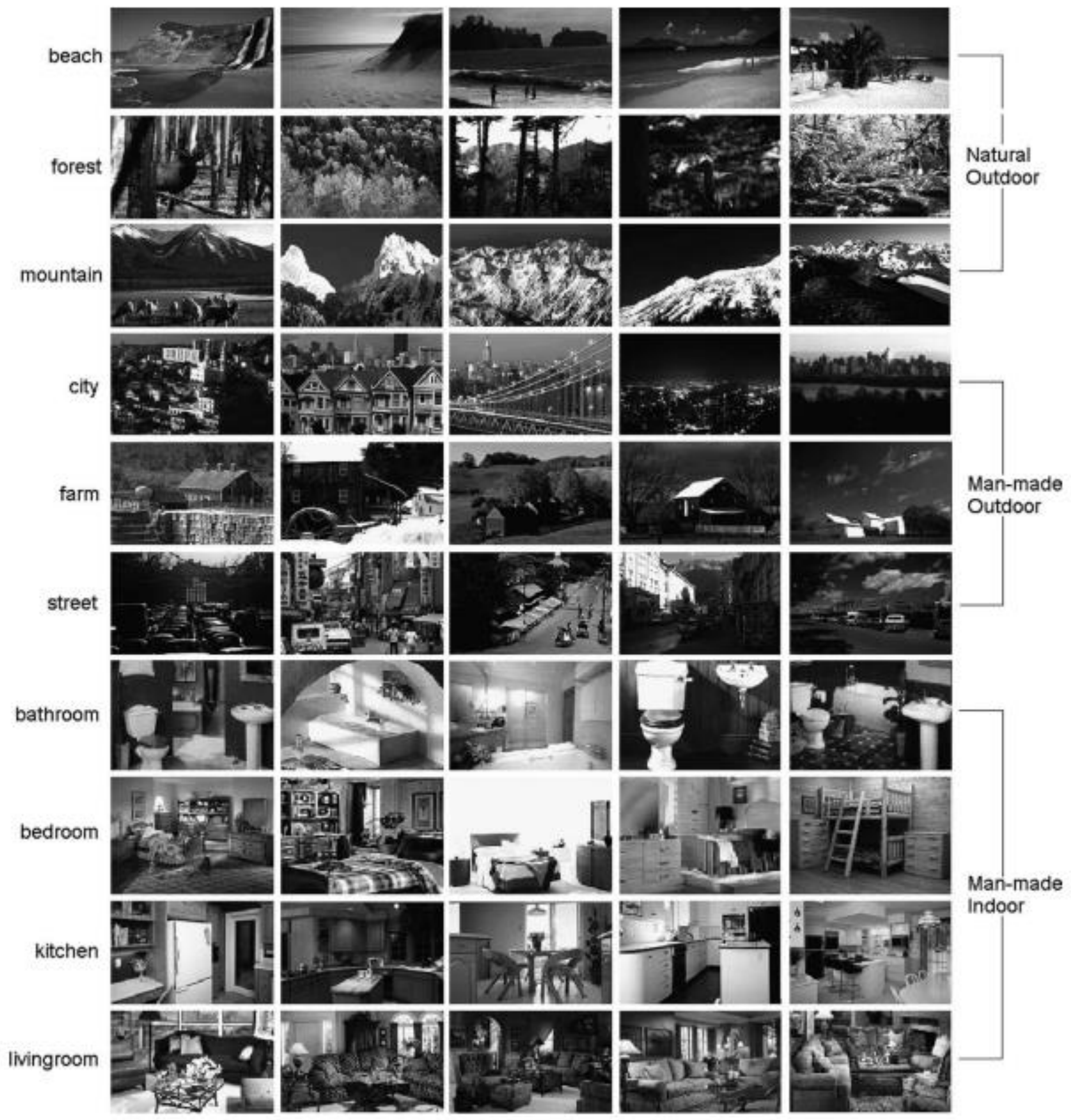
Color vs. Texture distribution





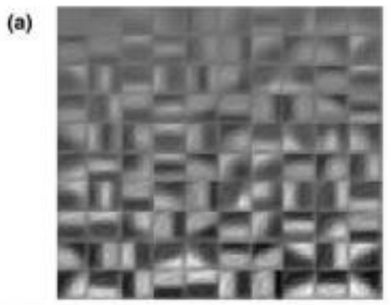
- These matched images look very similar in terms of their color distributions.
- Can texture distributions help distinguish them better?

Application: Scene classification



Renninger & Malik, 2004

Application: Scene classification



100 types of textures were found (by clustering) $\Longrightarrow$ called "**universal textons**"

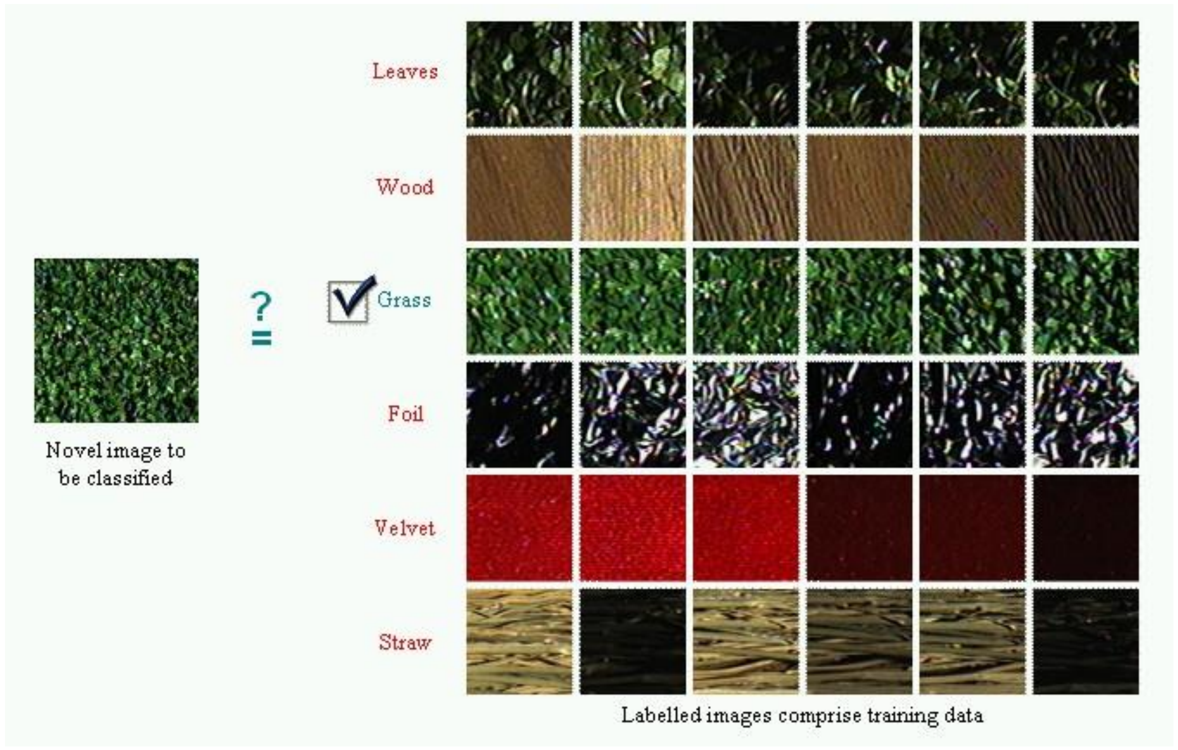
Assign each pixel to nearest texton
Build histogram of textons

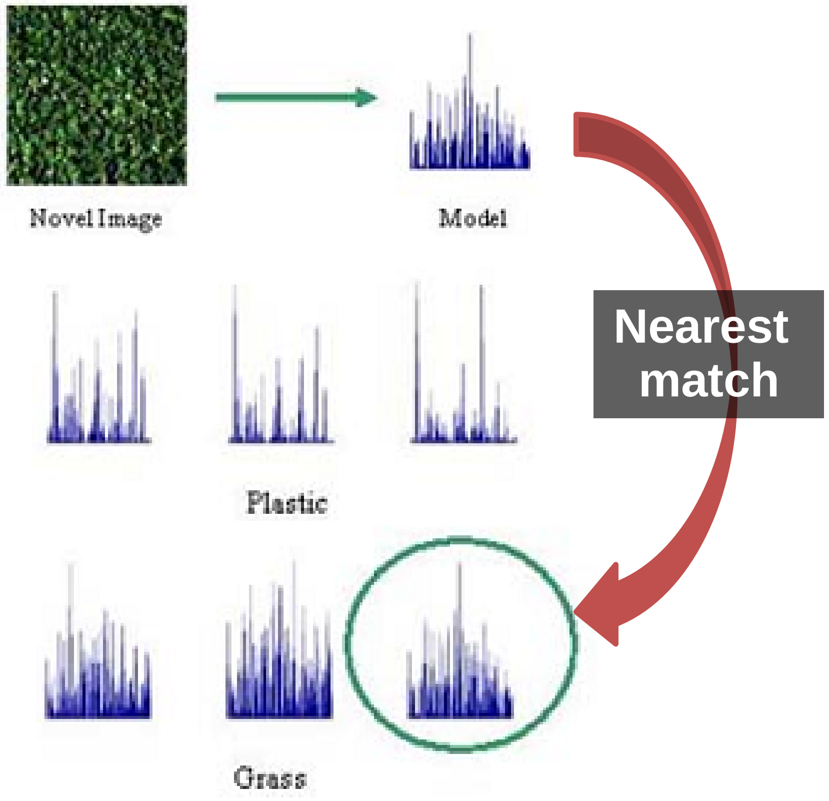
Classification by **chi square,** χ^2 measure to match texton histogram against stored examples. Take the nearest match.

$$\chi^2(h_i, h_j) = \frac{1}{2}\sum_{k=1}^{K}\frac{[h_i(k) - h_j(k)]^2}{h_i(k) + h_j(k)}$$

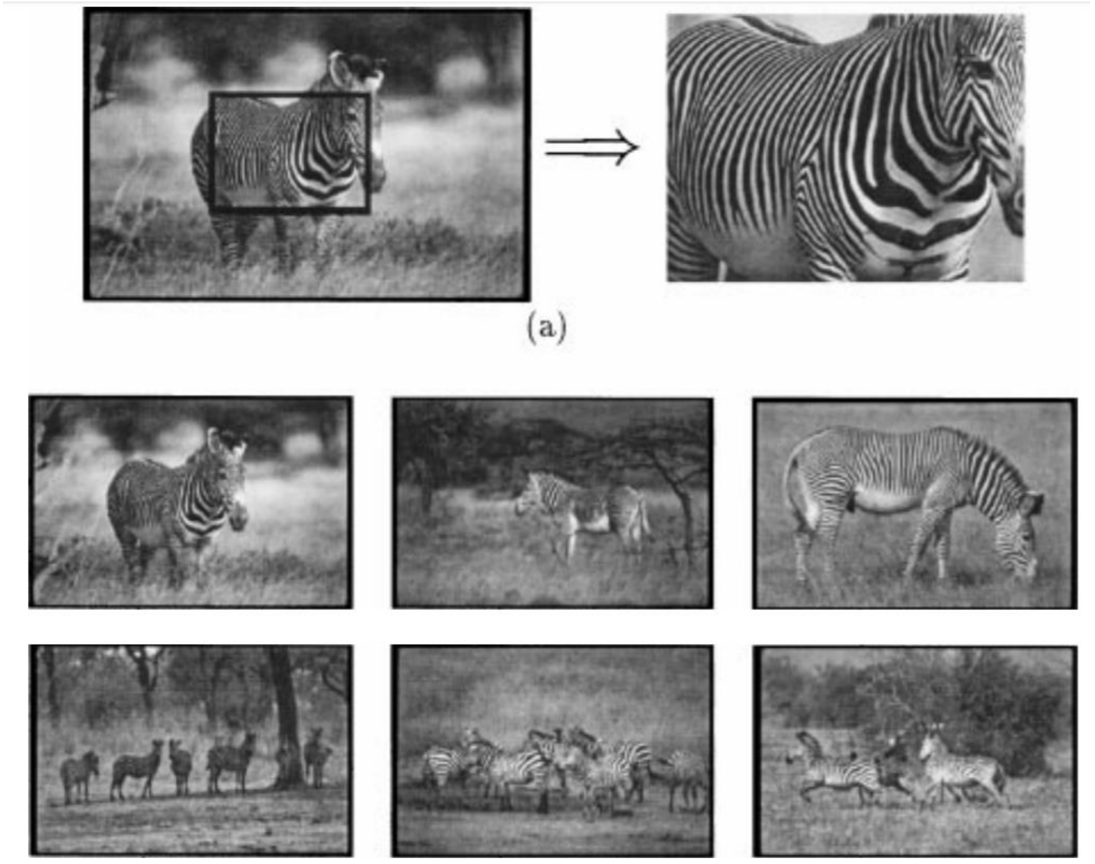
Arguably better than Euclidean distance!

Application: Material classification


Novel image to be classified
?=
✓ Grass
Leaves
Wood
Foil
Velvet
Straw
Labelled images comprise training data



Application: Image Retrieval



Texture features
for image retrieval

Introduction to
Earth Mover's distance

Y. Rubner, C. Tomasi, and L. J. Guibas. The earth mover's distance as a metric for image retrieval. *International Journal of Computer Vision*, 40(2):99-121, November 2000,

Summary

- **Textures** – defining them, representing them
- **Texture Representation**
  - Simple features (mean, std. dev.) from filters
  - Filter bank – a series of filters
  - Histogram of texture feature occurrences
- **Applications**: Scene classification, texture matching, image retrieval

Recommended Reading

- [Forsyth & Ponce] Chapter 10 (10.1 in particular)