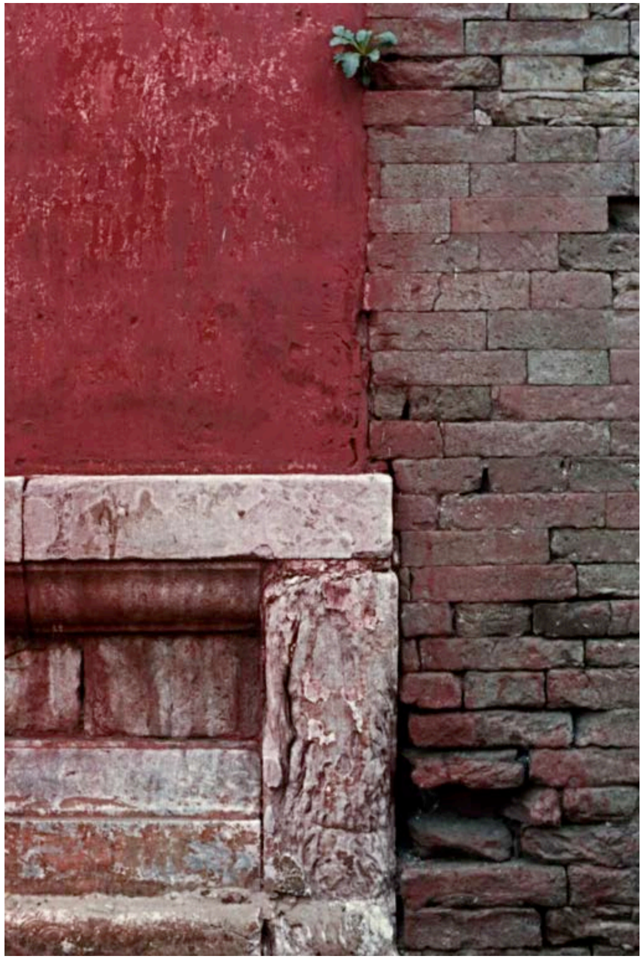
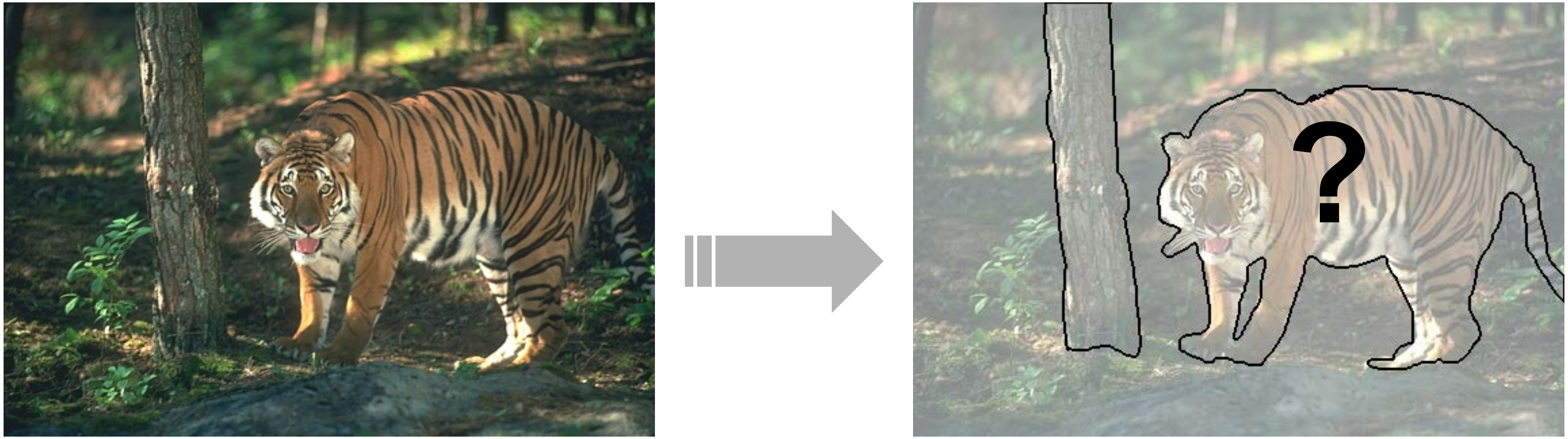
TEXTURE

- What is texture?
- Texture analysis
- Deep Texture



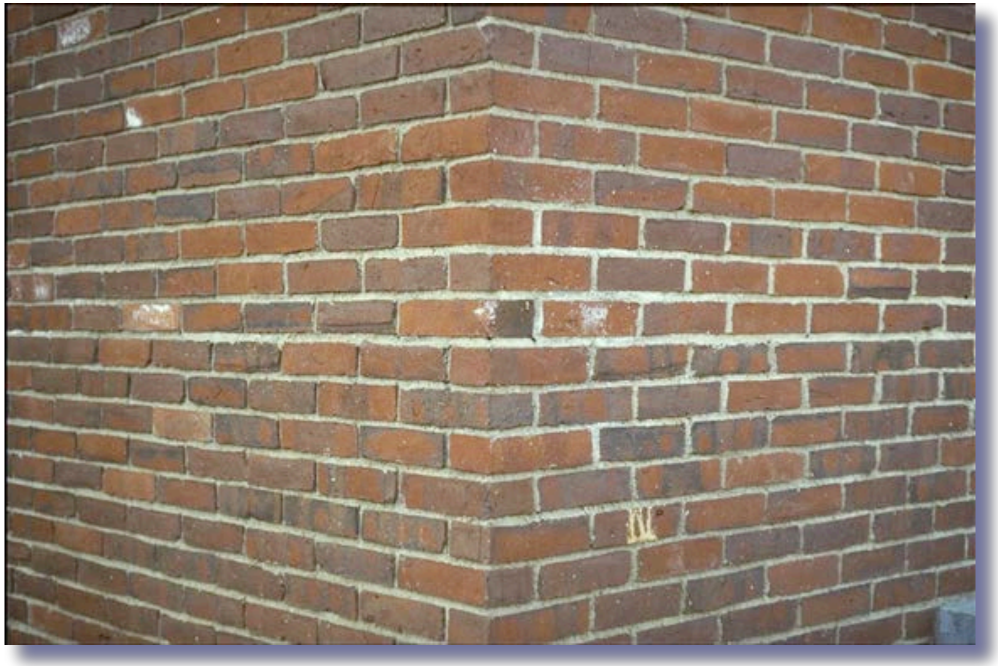
HOMOGENEOUS OR NOT?

TEXTURAL IMAGES



- Assign to individual pixels whose texture is similar the same values to form a textural image.
- Evaluate homogeneity both in the original image and in the textural one.

TEXTURE BOUNDARIES



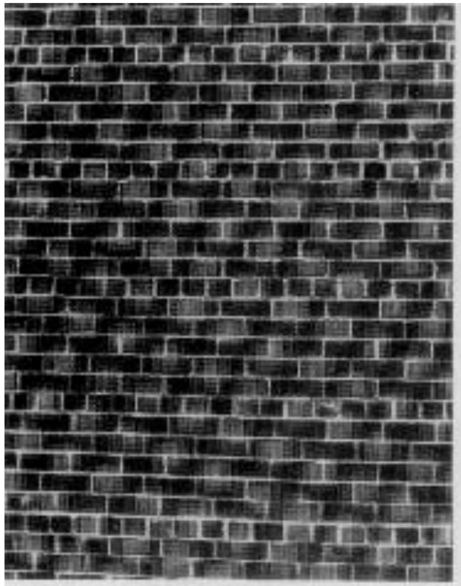
WHAT IS TEXTURE?

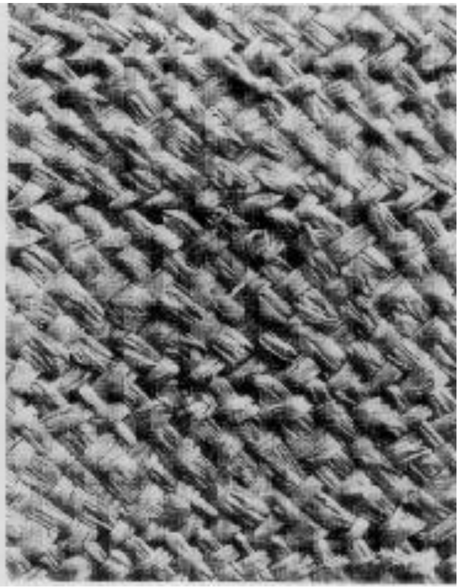
Repetition of a basic pattern:

- Structural
- Statistical

→ Non local property, subject to distortions.

STRUCTURAL TEXTURES

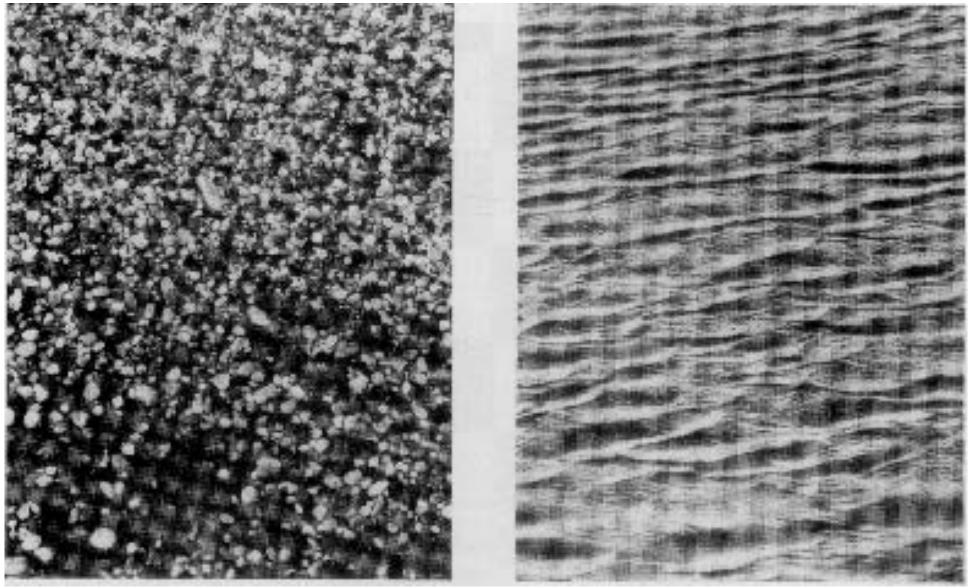




Repetitive Texture Elements (Texels)

A texel represents the smallest graphical element in a two-dimensional texture that creates the impression of a textured surface.

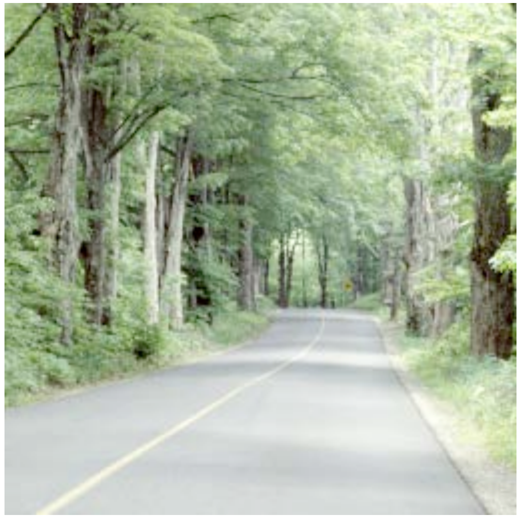
STATISTICAL TEXTURES



Homogeneous Statistical Properties

STRUCTURAL vs STATISTICAL

Segmenting out texels is difficult or impossible in most real images.



What are the fundamental texture primitives in this image?

Numeric quantities or statistics that describe a texture can be computed from the gray levels or colors alone.

→ This approach is less intuitive, but computationally more efficient.

TEXTURED vs SMOOTH

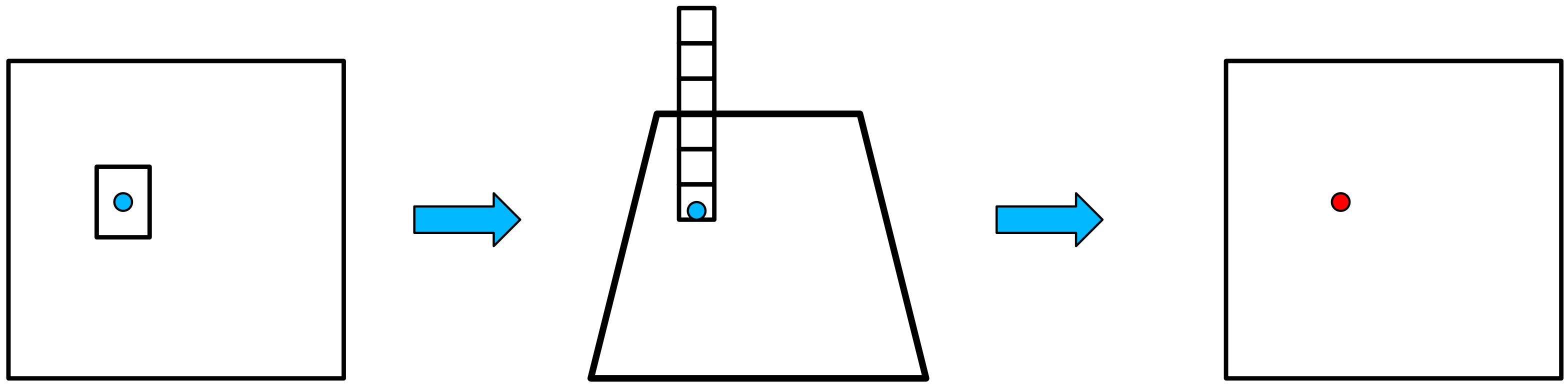
A “featureless” surface can be regarded as the most elementary spatial texture:

- Microstructures define reflectance properties.
- They may be uniform or smoothly varying.

→ Texture is a scale dependent phenomenon

SCALE DEPENDENCE

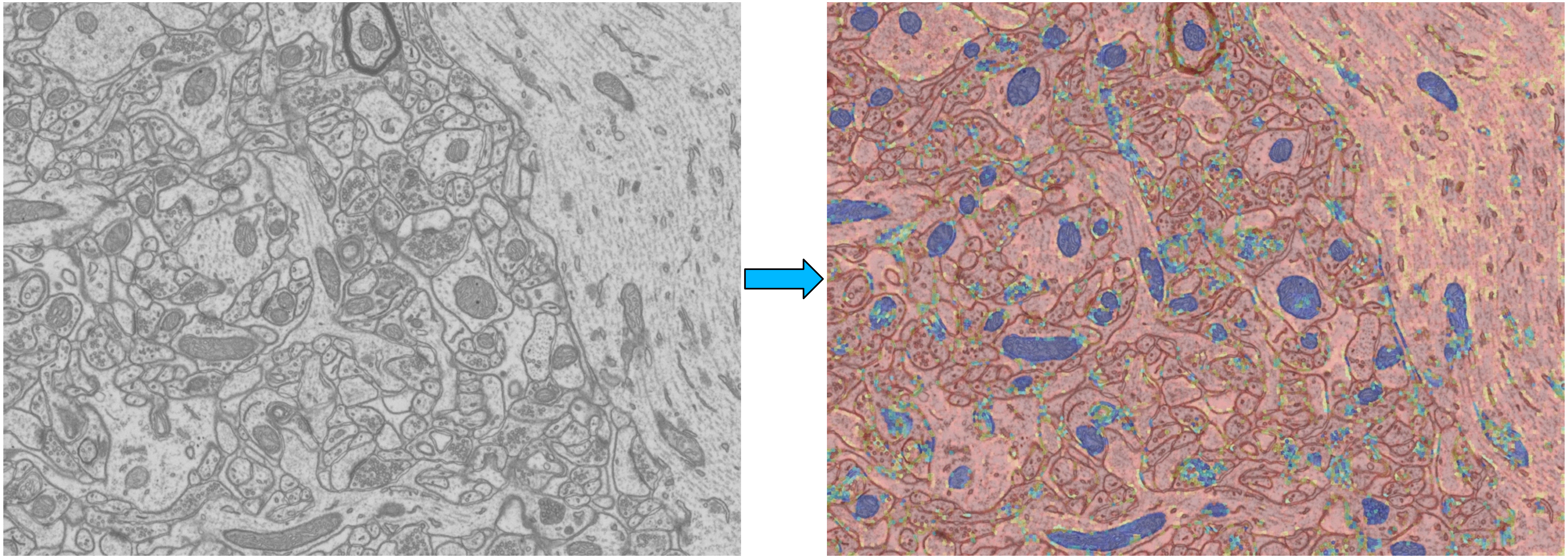
CREATING TEXTURAL IMAGES



Because texture is non-local, the texture of individual pixels must be estimated using neighborhoods surrounding them:

- For each pixel, compute a feature vector using either an image patch or a set of filters.
- Run a classification algorithm to assign a texture value to each pixel.

MITOCHONDRIA



PATCH-BASED MEASURES

Spectral metrics:

- Texture characterized by properties of its Fourier transform.

Statistical Metrics:

- Texture is a quantitative measure of the arrangement of intensities in a region.
- Can be modeled as a Markov Process.

DISCRETE FOURIER TRANSFORM

$$F(\mu,\nu) = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\exp(-2i\pi(\mu x/M + \nu y/N))$$

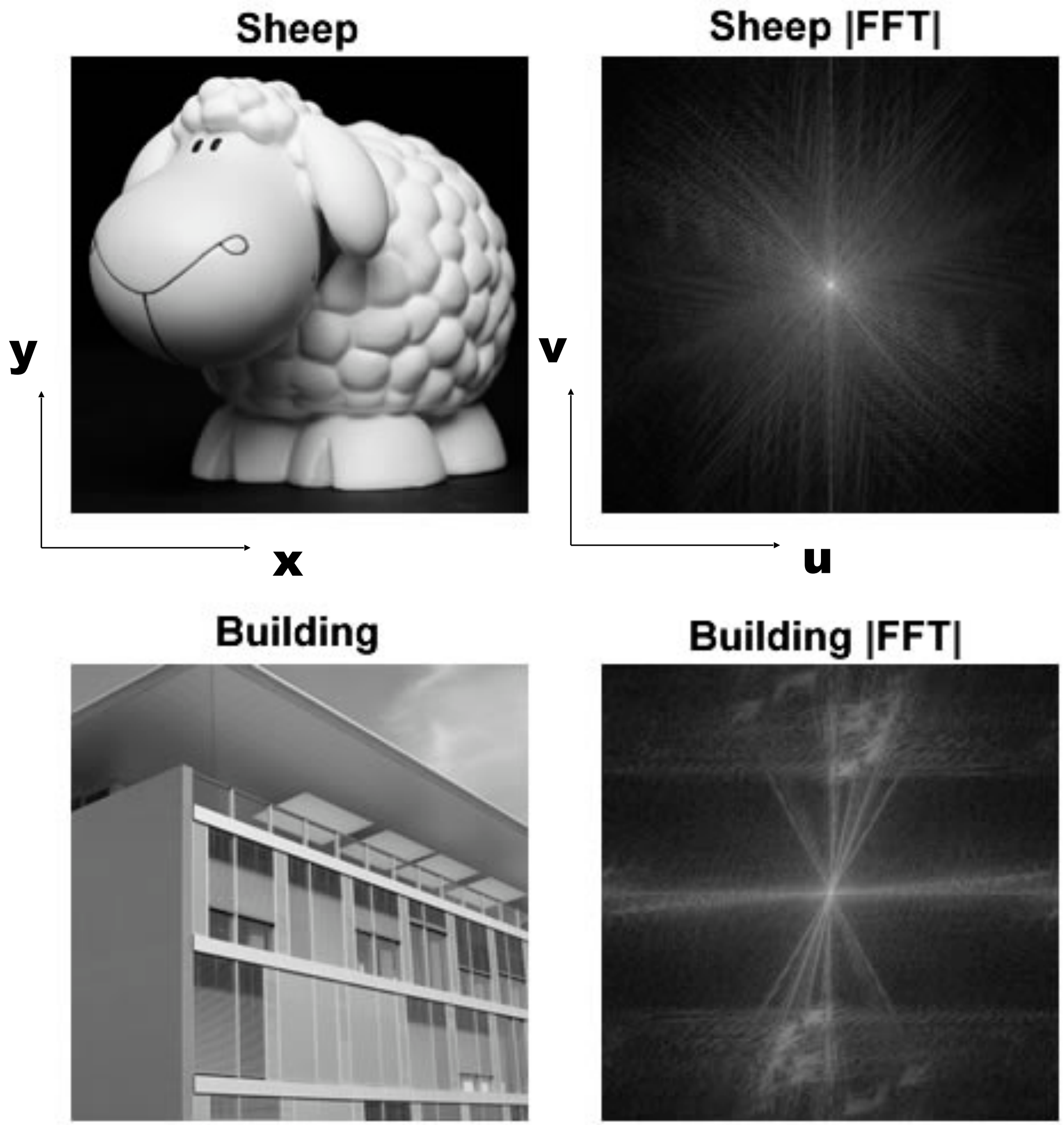
$$f(x,y) = \frac{1}{MN}\sum_{\mu=0}^{M-1}\sum_{\nu=0}^{N-1} F(\mu,\nu)\exp(+2i\pi(\mu x/M + \nu y/N))$$

- The DFT of f * g is the product of the DFT of f with the DFT of g.
- The DFT of a symmetric function is real.

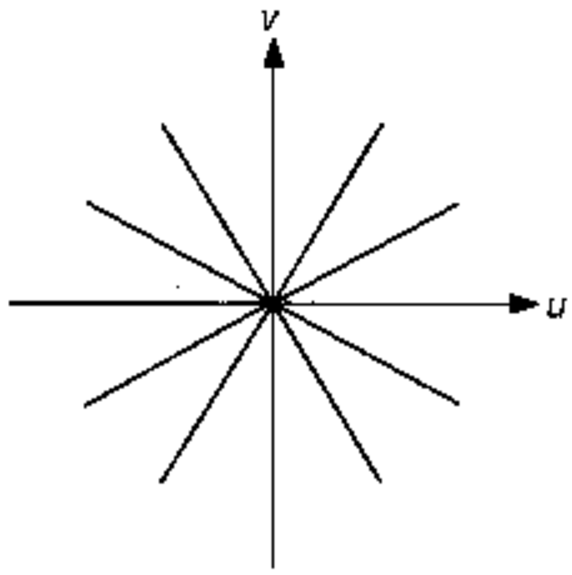
Bracewell, chap. 11

SPECTRAL ANALYSIS

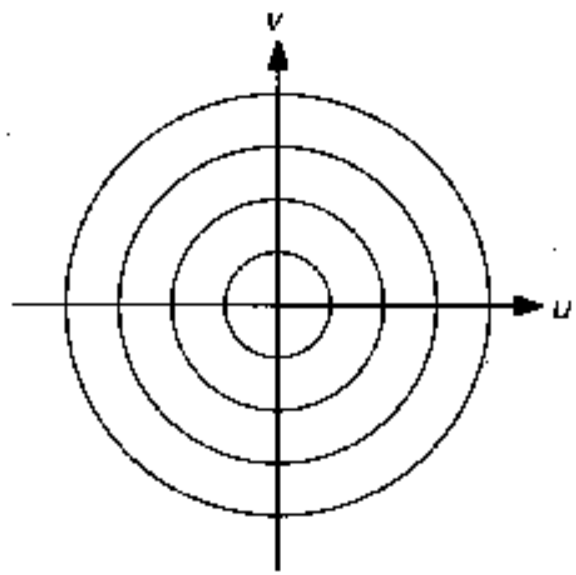
The magnitude of the DFT captures the main orientations in the image.



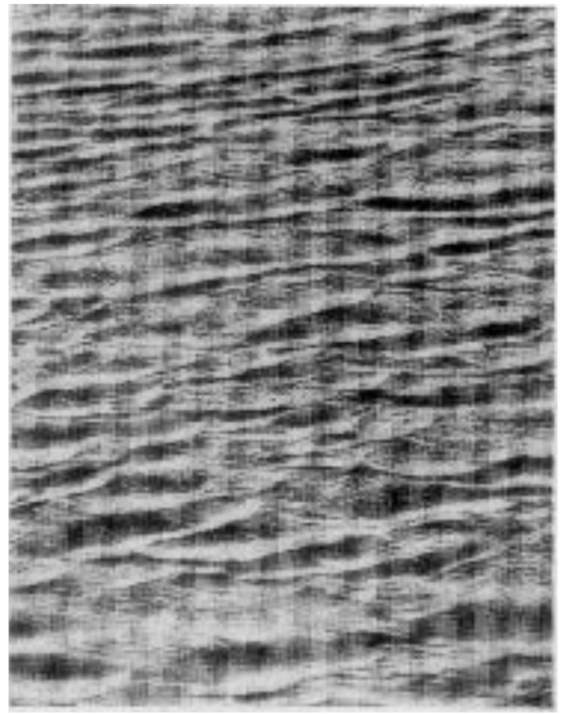
TEXTURE ANALYSIS



Angular Bins

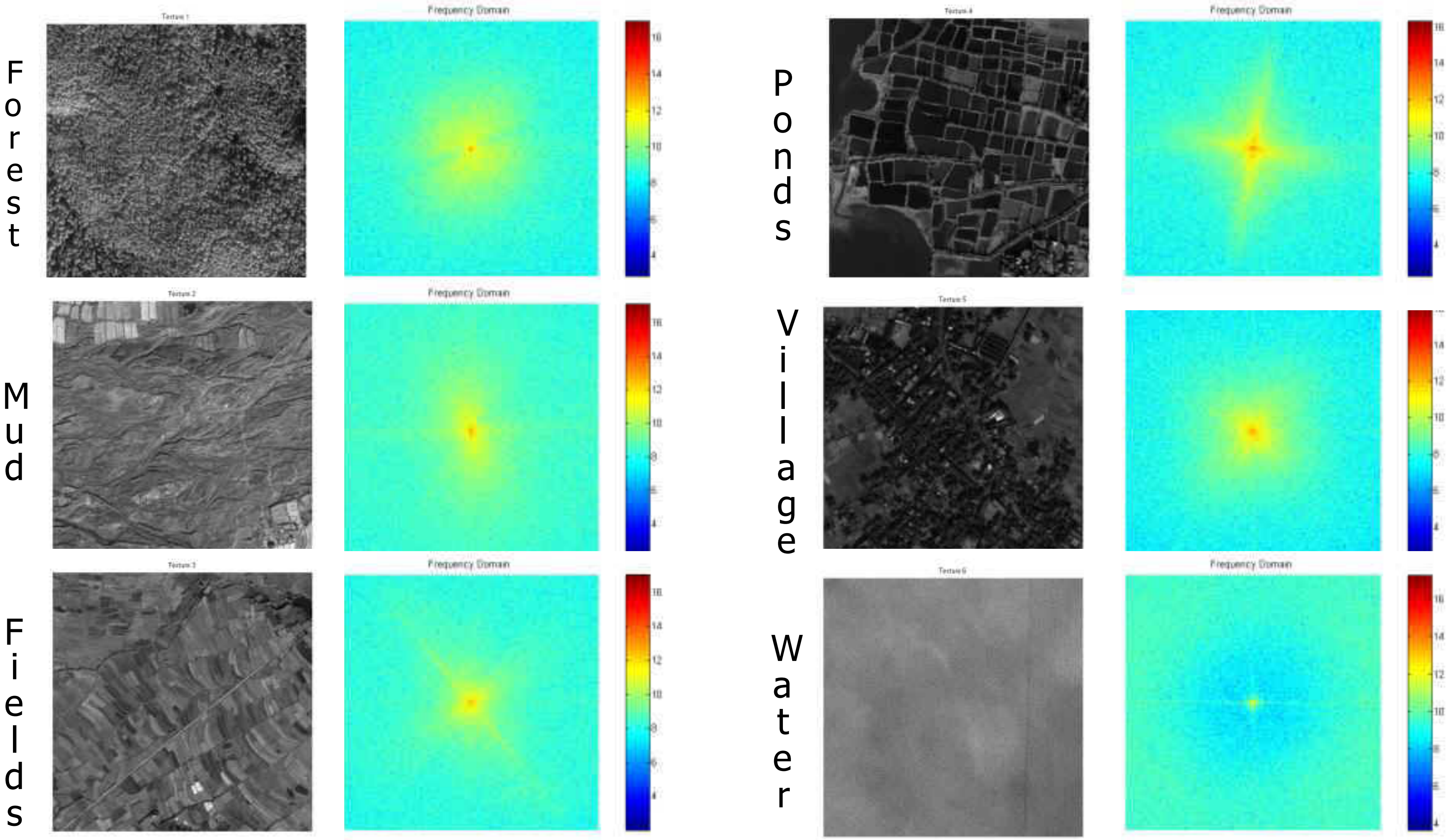


Radial Bins



Angular and radial bins in the Fourier domain capture the directionality and rapidity of fluctuation of an image texture.

TEXTURE CLASSIFICATION



LIMITATIONS

- DFT on small patches is subject to severe boundary effects.
- Only applicable if texture is uniform over large areas.
- Improved results by using wavelets instead.

STATISTICAL METRICS

Most natural textures are best modeled using such methods.

First order gray-level statistics:

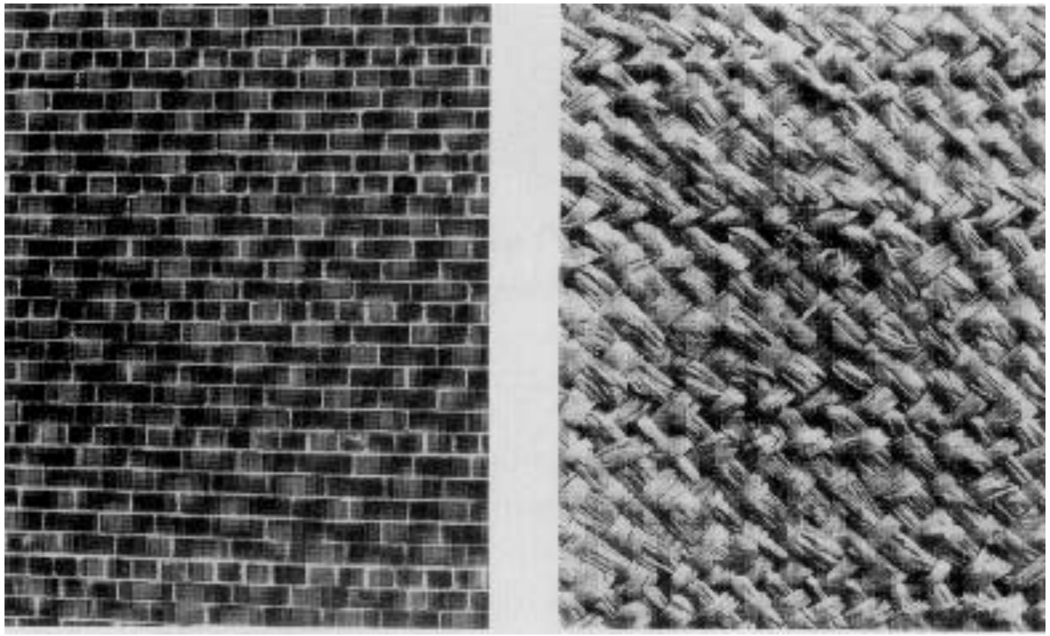
- Statistics of single pixels in terms of histograms.
- Insensitive to neighborhood relationships.

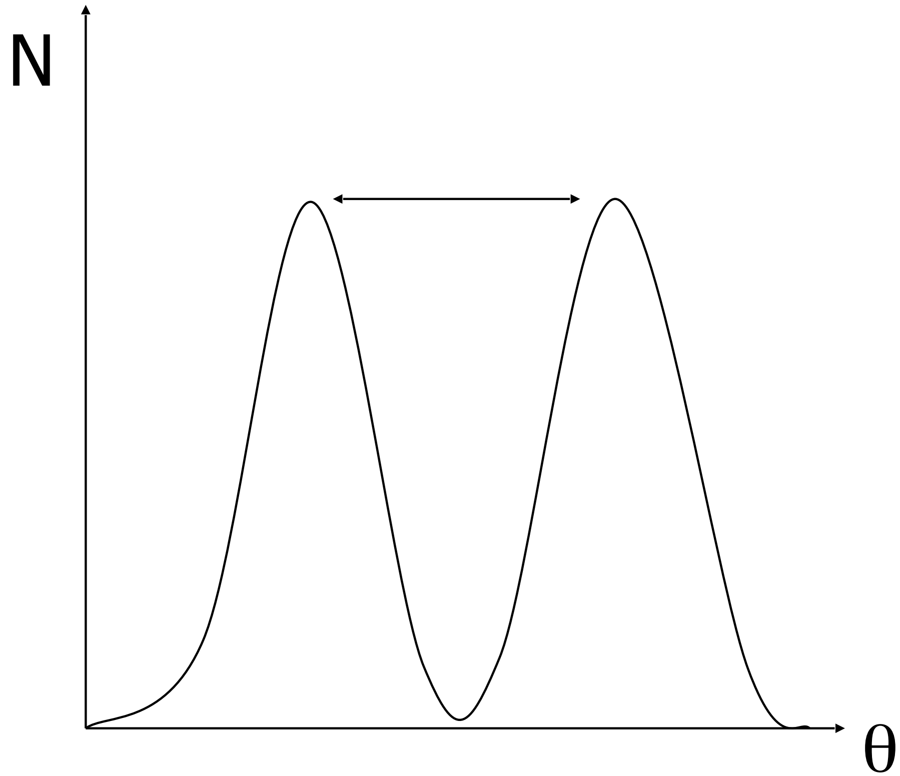
Second order gray-level statistics:

$$P(l, m, \Delta i, \Delta j) : P(i, j) = l \text{ and } P(i + \Delta i, j + \Delta j) = m$$

Given g gray-levels, for each $(\Delta i, \Delta j)$, P is represented as the gxg matrix H.

FIRST ORDER TEXTURE





Orientation histogram gives a clue to the orientation of the underlying plane.

FIRST ORDER MEASURES

Edge Density and Direction

- Edge detection as a first step in texture analysis.
- The number of edge pixels in a fixed-size region tells us how busy that region is.
- The directions of the edges also help characterize the texture

Edgeness per unit area

- { p | gradient_magnitude(p) ≥ threshold}| / N where N is the unit area or region.

Edge magnitude and direction histograms

- Fmagdir = (Hmagnitude, Hdirection)

SECOND ORDER MEASURES

Histogram of the co-occurrence of particular intensity values in the image.

- Specified in terms of geometric relationships between pixel pairs:
  - Distance
  - Orientation

- $P(i,j,d,\theta)$ Frequency with which a pixel with value j occurs at distance d and orientation θ from a pixel with value i.

SIMPLE EXAMPLE

$$\text{If} \qquad I = \begin{bmatrix} 0 & 1 & 2 & 3 & 1 \\ 2 & 1 & 3 & 1 & 1 \\ 0 & 0 & 2 & 2 & 1 \\ 1 & 2 & 0 & 3 & 1 \\ 0 & 0 & 0 & 0 & 3 \end{bmatrix},$$

$$\text{then} \qquad H = \begin{bmatrix} 4 & 1 & 1 & 2 \\ 0 & 1 & 2 & 1 \\ 1 & 2 & 1 & 1 \\ 0 & 3 & 0 & 0 \end{bmatrix},$$

$$\text{and } P(l, m, 1, 0) = \frac{H(l, m)}{20}.$$

CO-OCURRENCE MATRIX

No need to distinguish between

$$P(m, l, \Delta i, \Delta j)$$

and

$$P(l, m, \Delta i, \Delta j)$$

→ Co-Occurrence matrix C:

$$C = H + H^T$$

2ND ORDER TEXTURE MEASURES

Contrast:

$$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$$

Dissimilarity:

$$\sum_{i,j=0}^{N-1} P_{i,j}|i-j|$$

Homogeneity:

$$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$$

Angular Second Moment (Energy, Uniformity):

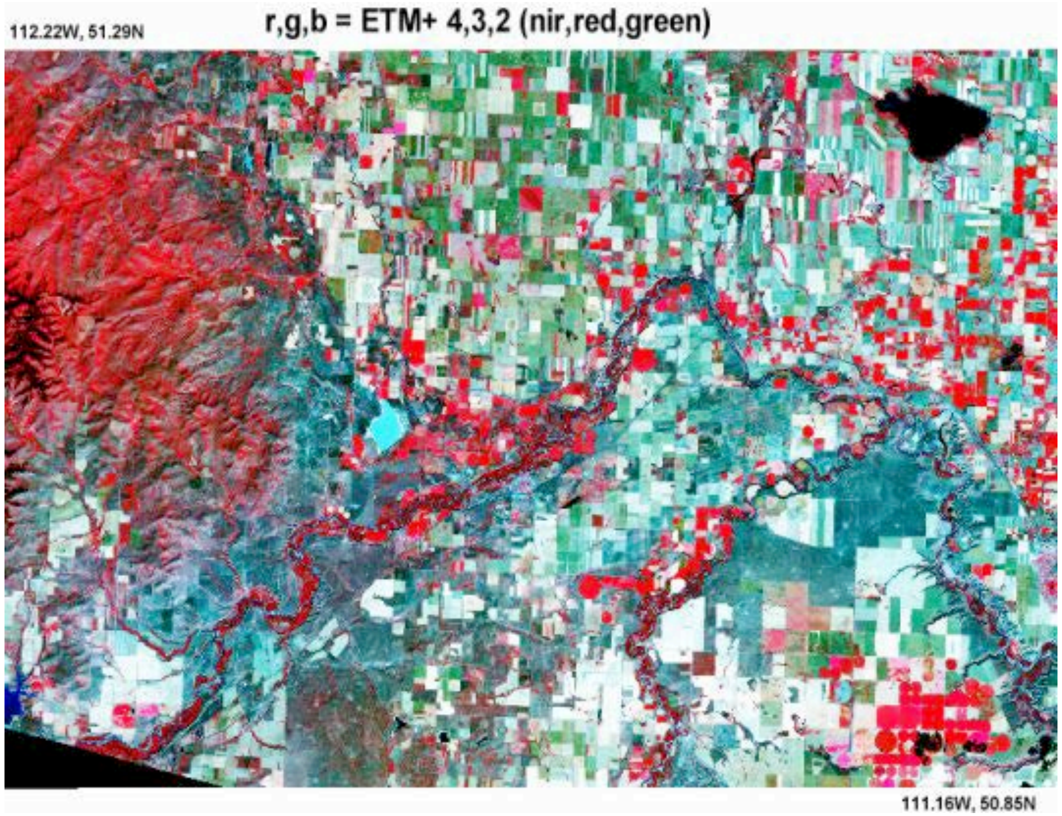
$$\sum_{i,j=0}^{N-1} P_{i,j}^2$$

Entropy:

$$\sum_{i,j=0}^{N-1} P_{i,j}(-\ln P_{i,j})$$

and many more ......

LANDSAT IMAGE

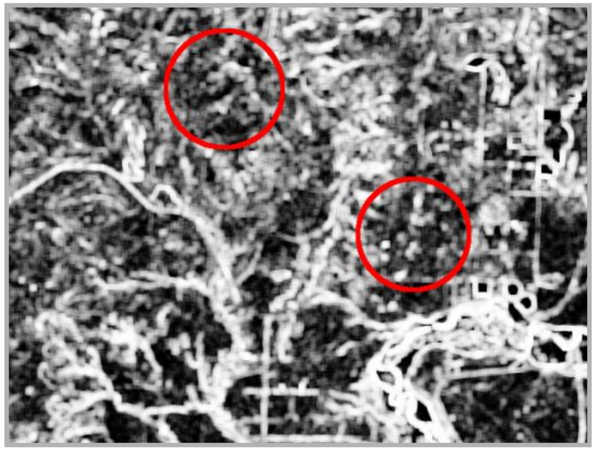


The image is excerpted from Path 41, Row 25 of Landsat 7 ETM+, dated 4 September 1999. This is an area in the Rocky Mountain Foothills near Waterton National Park, Alberta. The western edge of the image contains steep slopes and deep valleys. To the east is both grassland and annual crops, mostly grains. The eastern area is bisected by numerous small streams.

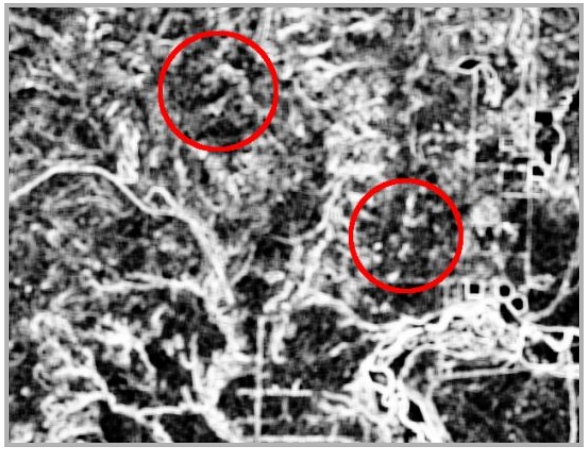
FULL RESOLUTION

COMPARISON

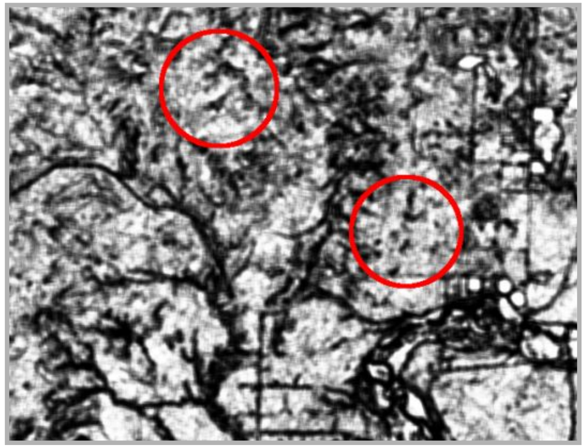
Contrast

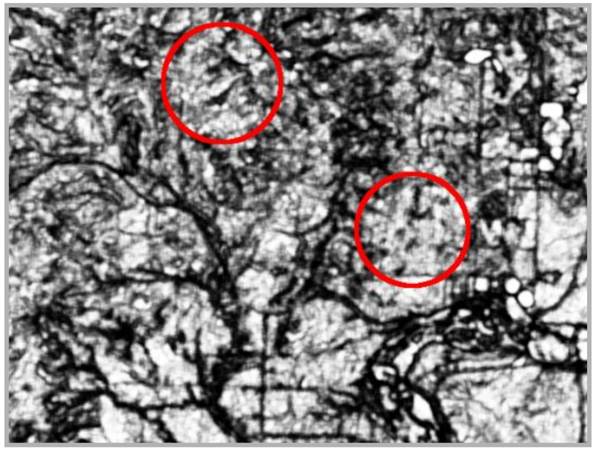


Dissimilarity

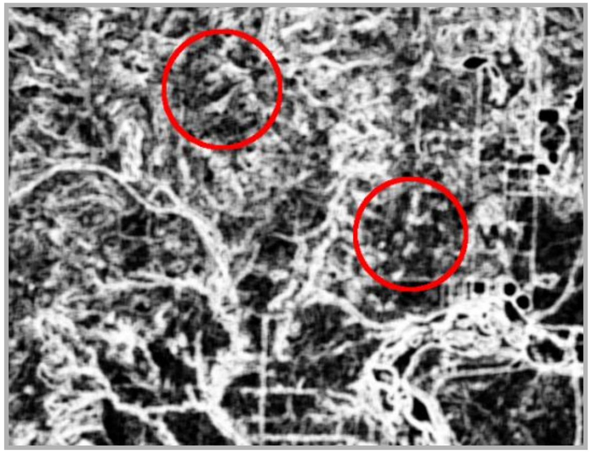


Homogeneity

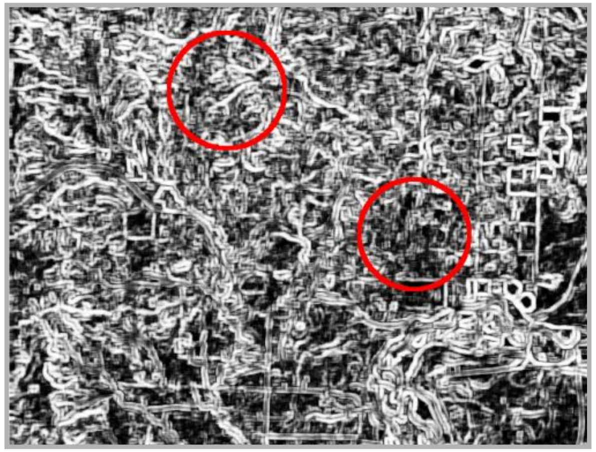




ASM



Entropy



Correlation

CLASSIFICATION

Used on aerial images to identify eight terrain classes:

- Old residential
- New residential
- Urban
- Lake
- Swamp
- Scrub
- Wood

AERIAL TEXTURES

PARAMETER CHOICES

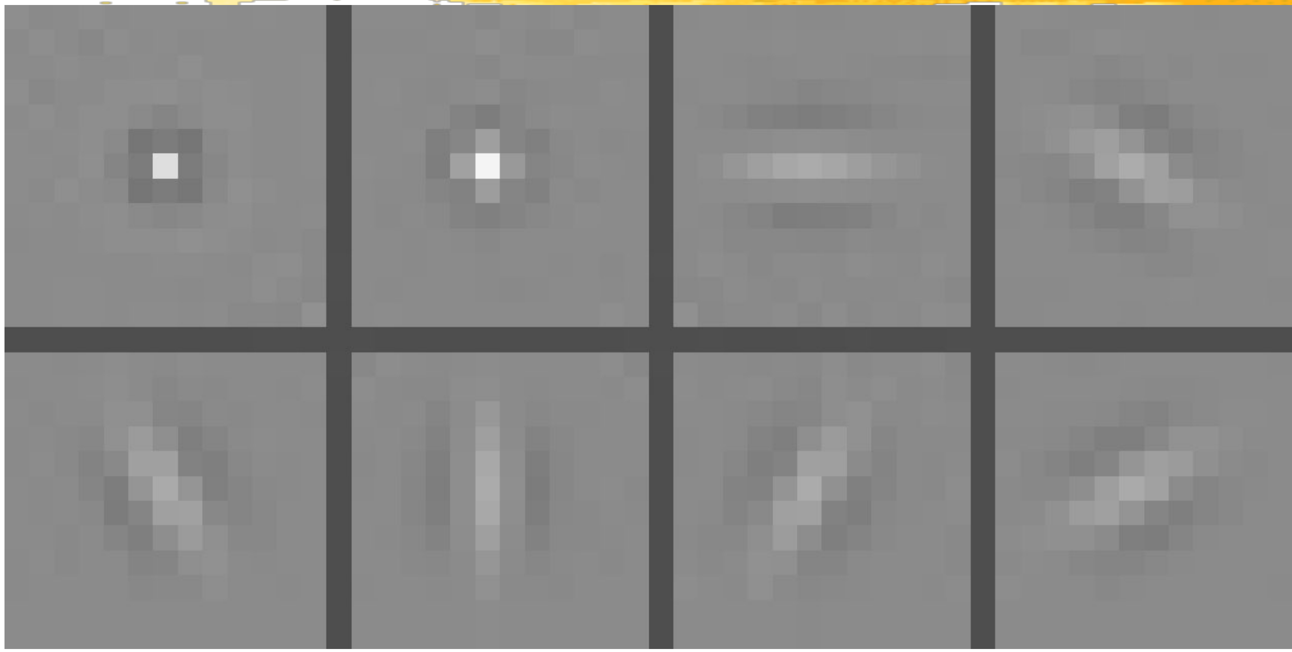
Using co-occurence matrices requires choosing:

- window size,
- direction of offset,
- offset distance,
- which channels to use,
- which measures to use.

How do we choose these parameters?

- Critical question for **all** statistical texture methods.
- Can be addressed using Machine Learning.

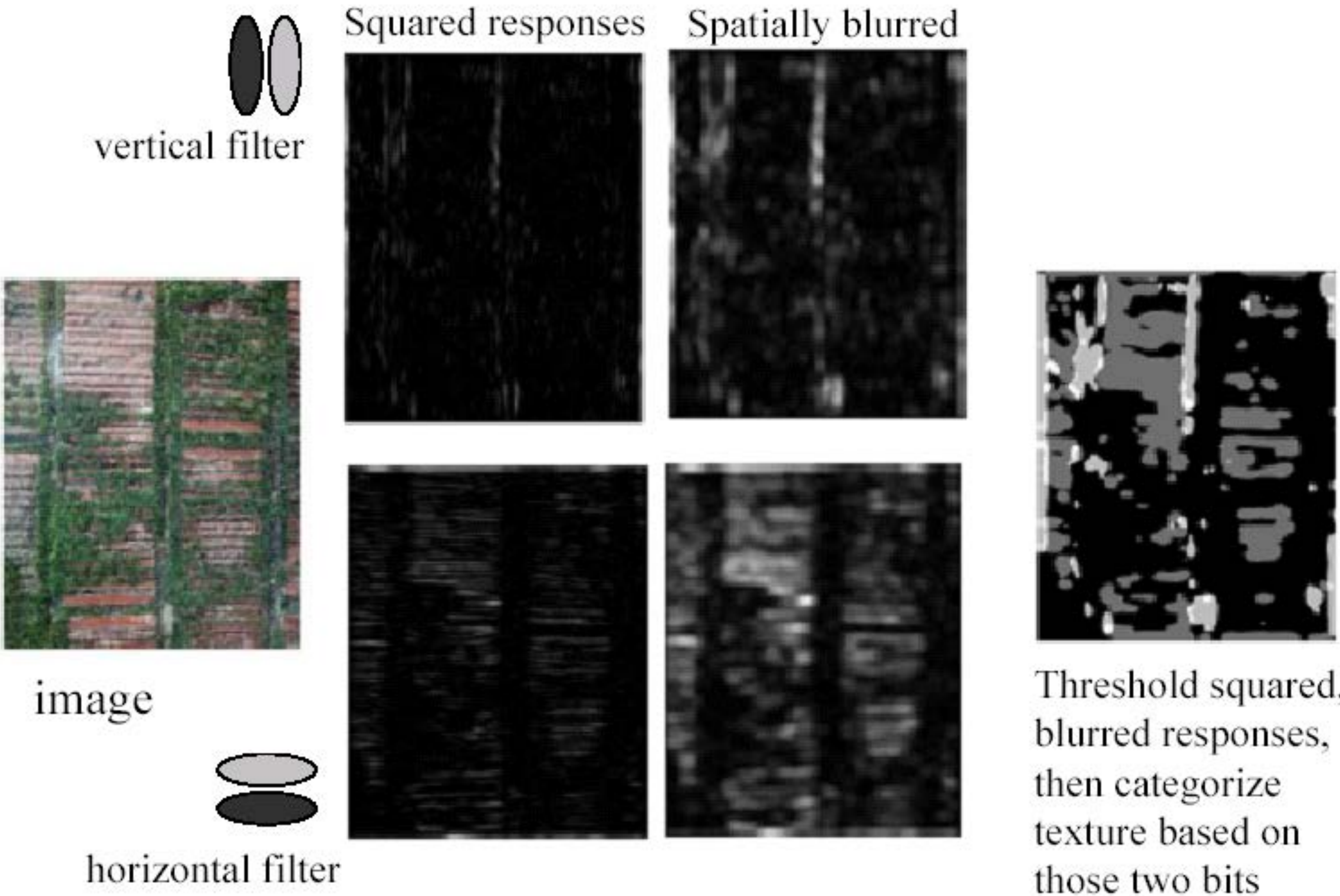
FILTER BASED MEASURES



Represent image textures using the responses of a collection of filters.

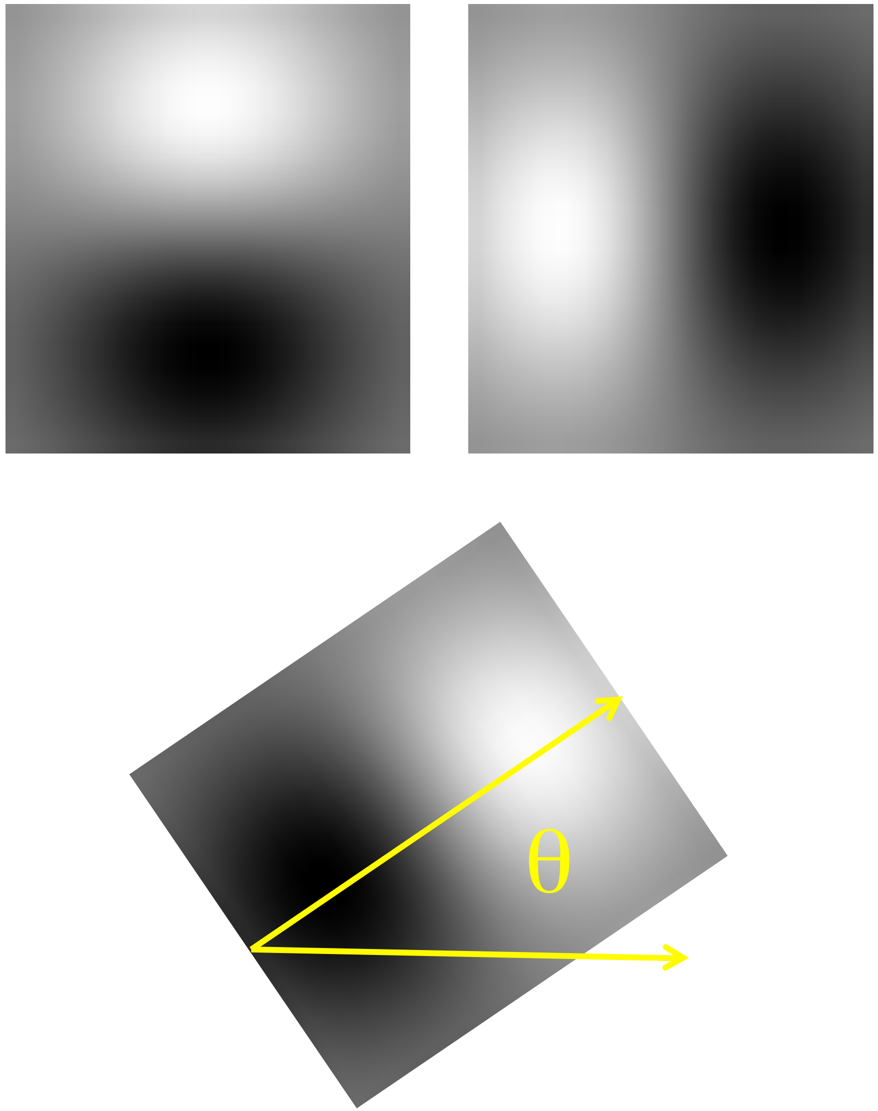
- An appropriate filter bank will extract useful information such as spots and edges
- Traditionally one or two spot filters and several oriented bar filters

HORIZONTAL AND VERTICAL STRUCTURES



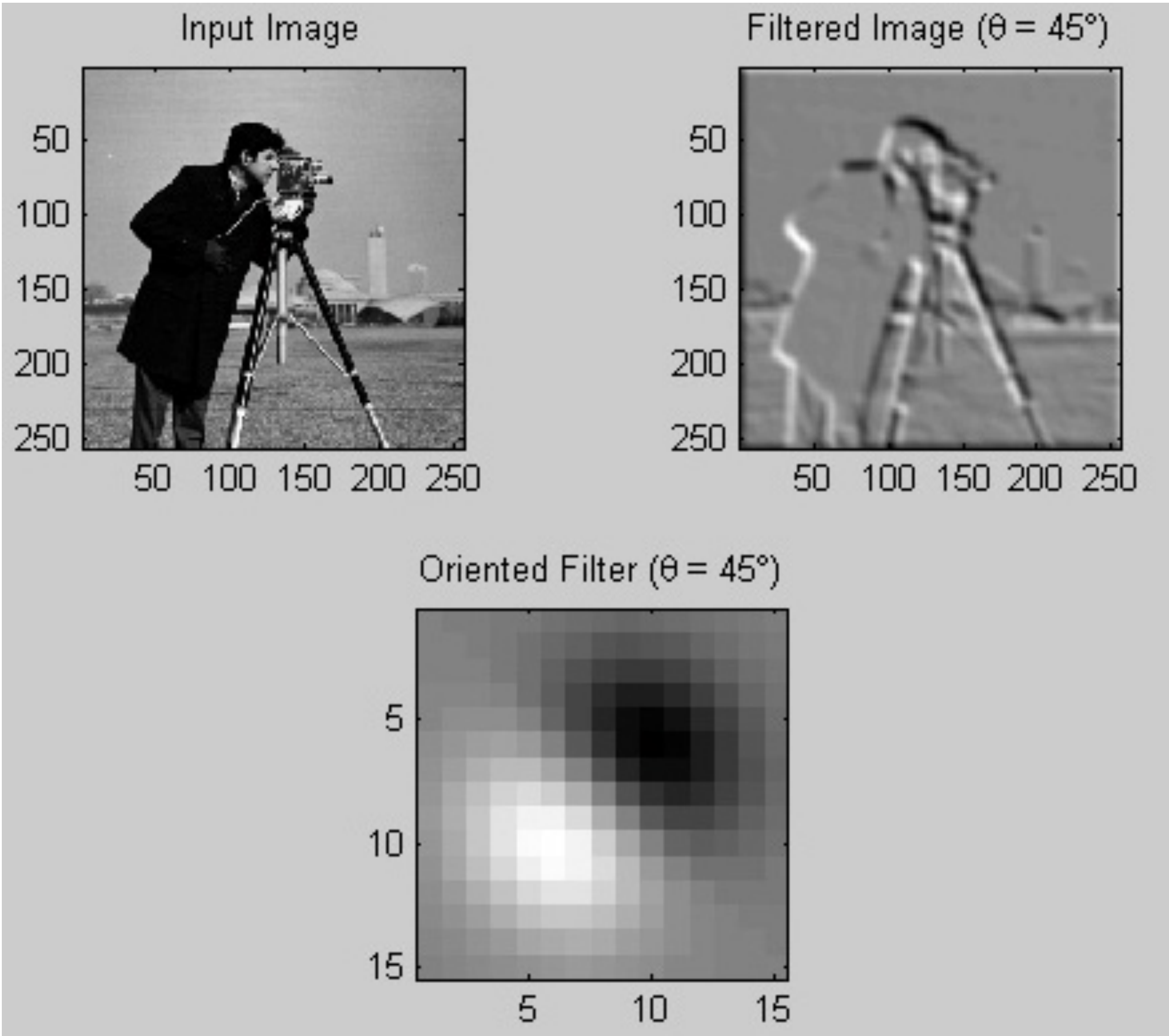
Threshold squared, blurred responses, then categorize texture based on those two bits

ORIENTED FILTERS

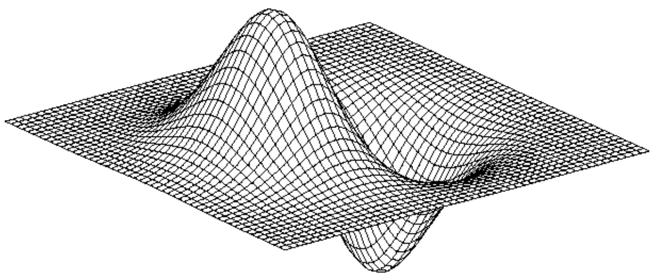


$$\frac{\partial I}{\partial \theta} = cos(\theta)\frac{\partial I}{\partial x} + sin(\theta)\frac{\partial I}{\partial y}$$

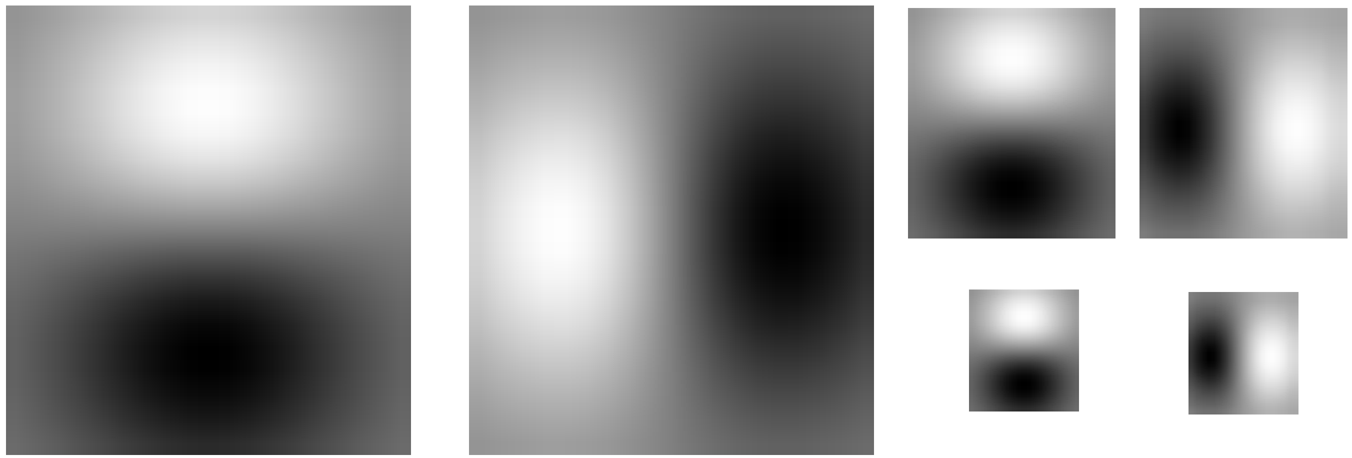
DIRECTIONAL GRADIENTS



GAUSSIAN FILTER DERIVATIVES

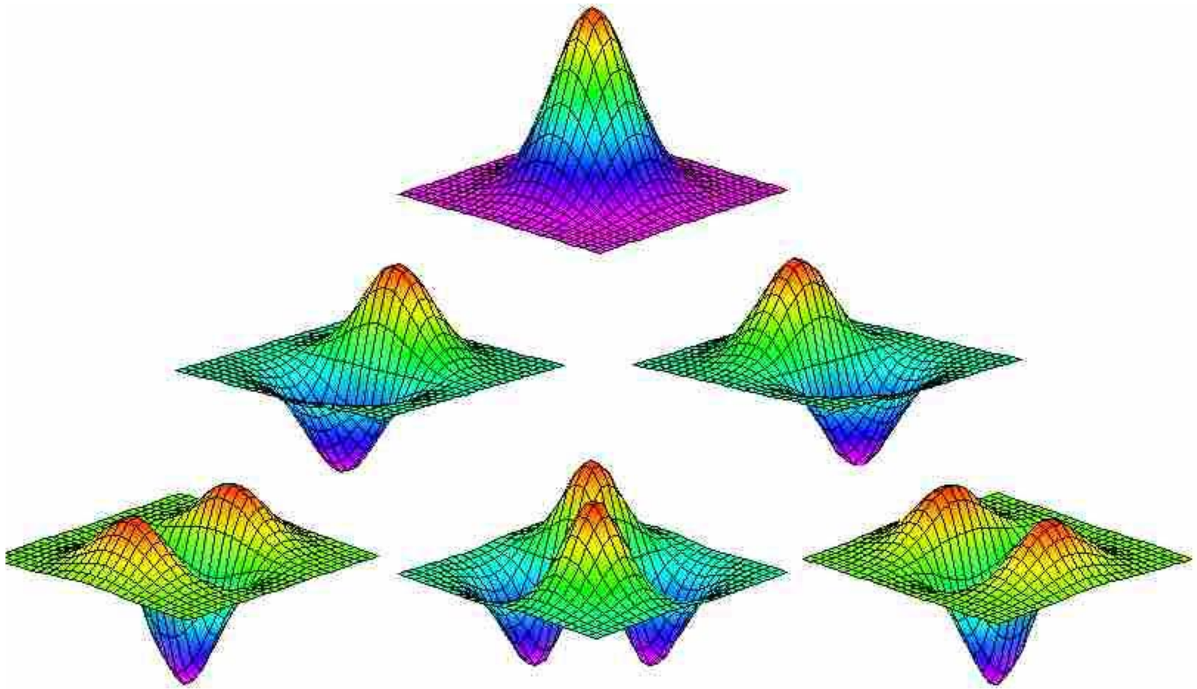


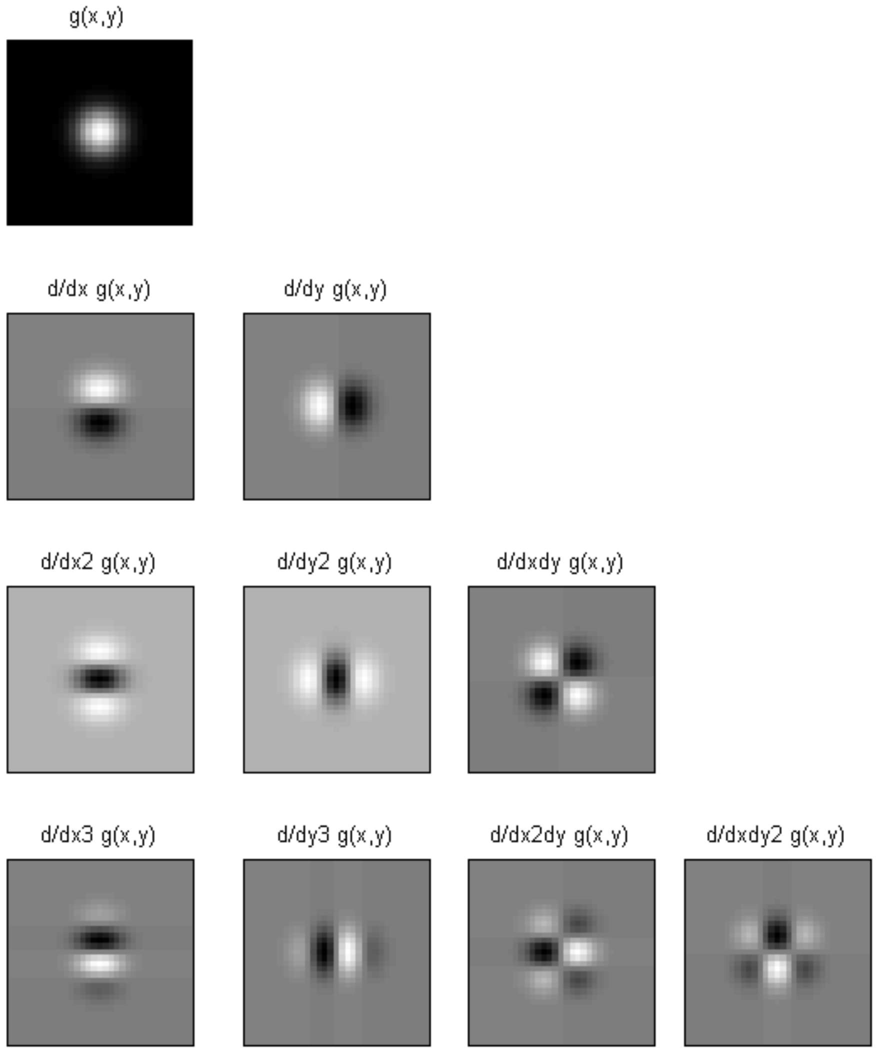
Gaussian Derivative



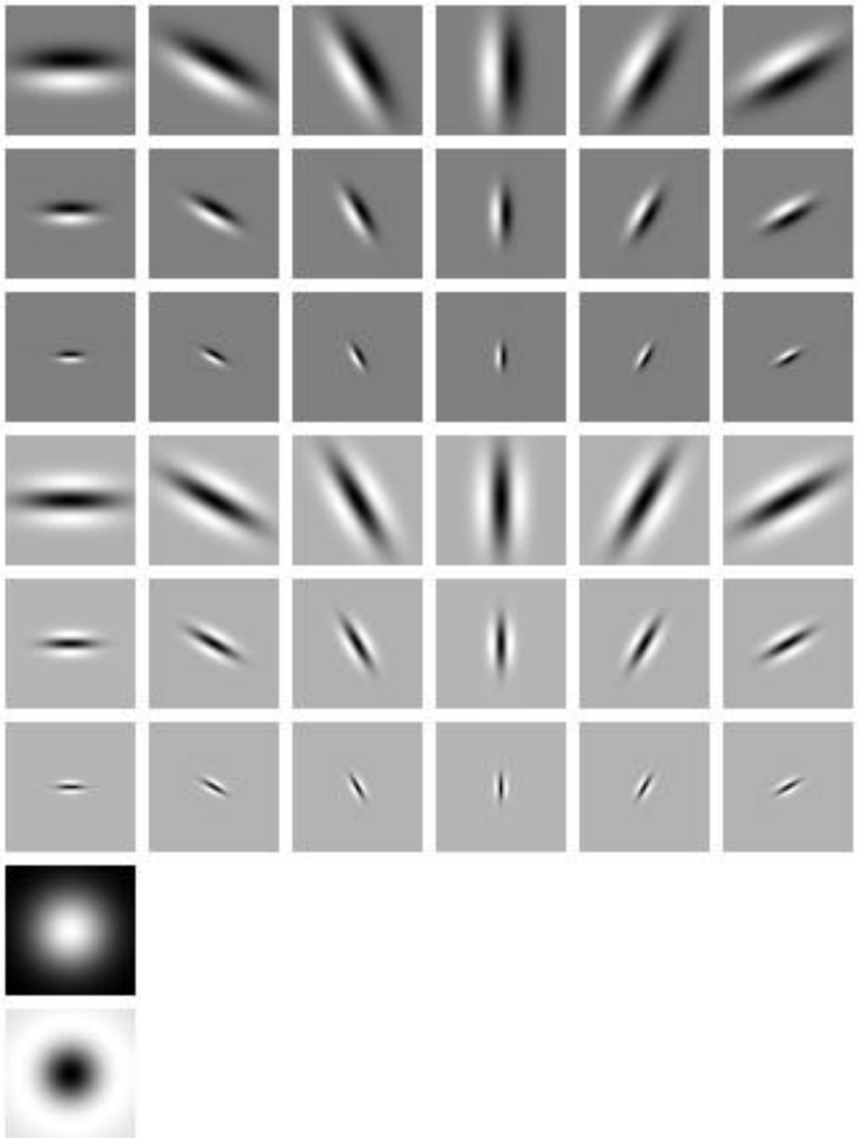
x and y derivatives at different scales

HIGHER ORDER DERIVATIVES



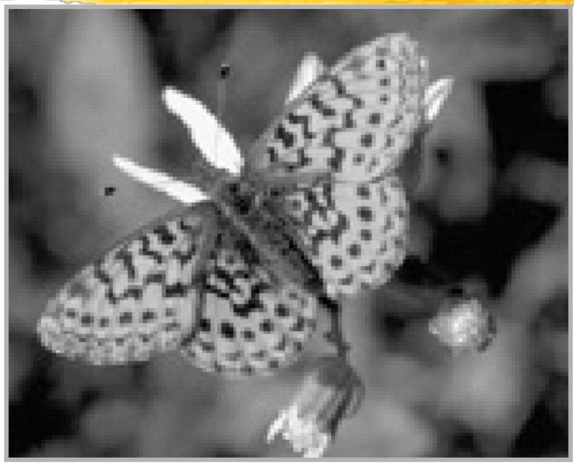


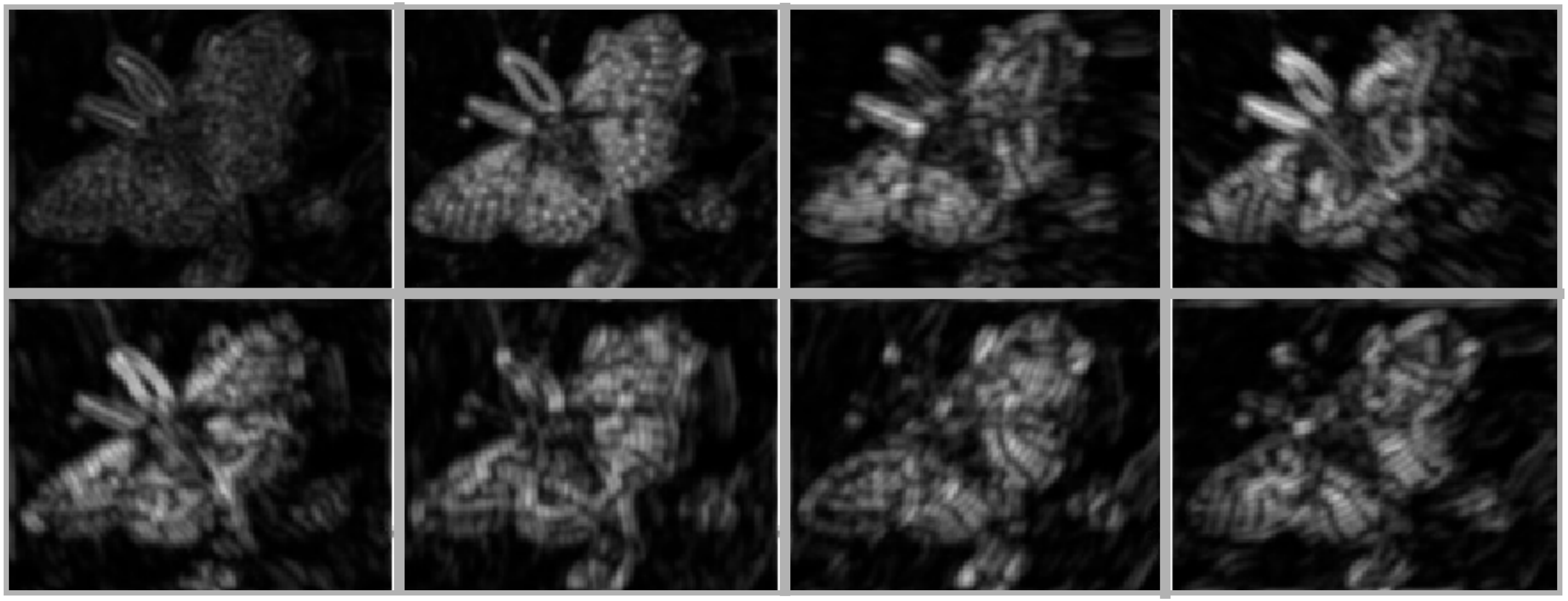
FILTER BANKS



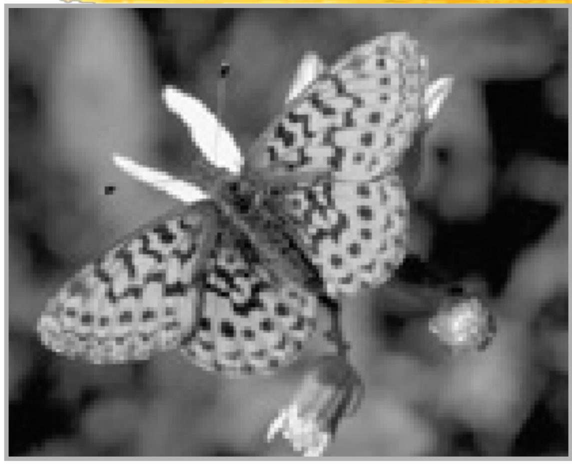
- Different scales.
- Different orientations.
- Derivatives order 0, 1, 2 ..

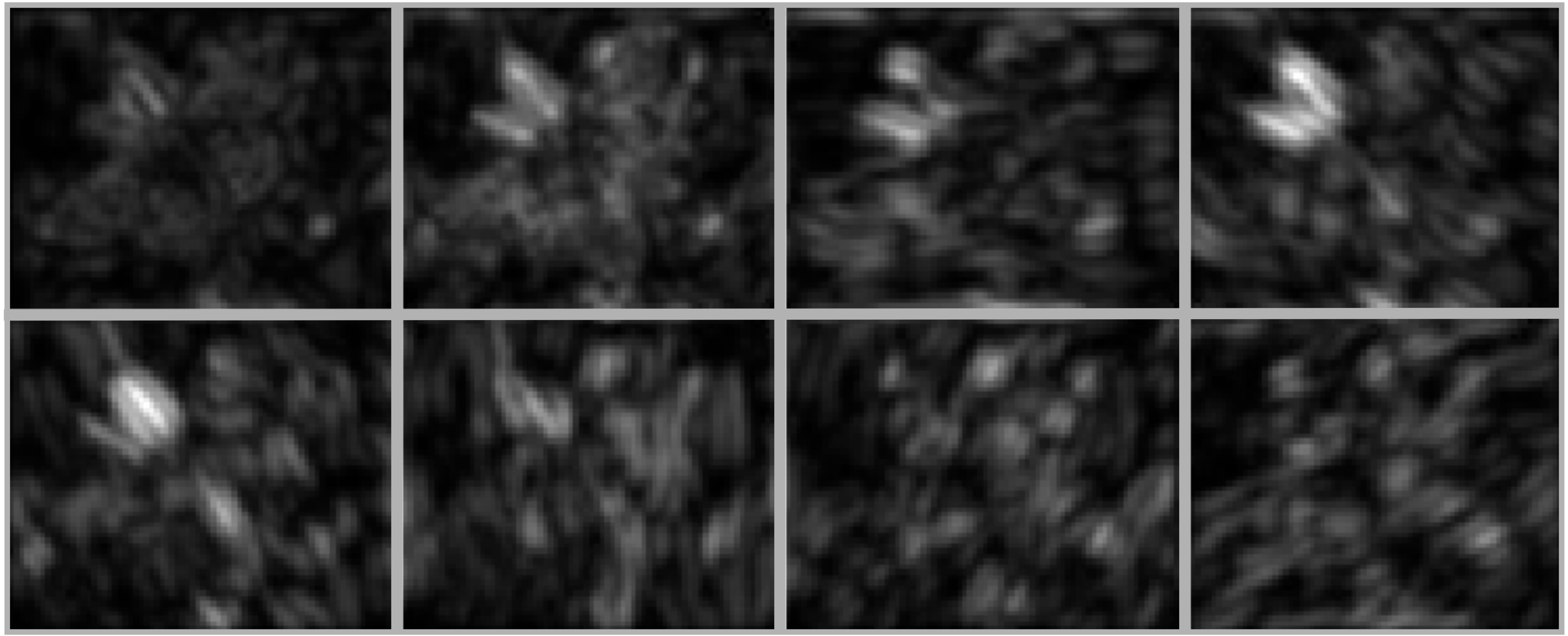
FILTER RESPONSES: HIGH RESOLUTION





FILTER RESPONSES: LOW RESOLUTION





GABOR FILTERS

Gabor filters are the products of a Gaussian filter with oriented sinusoids. They come in pairs, each consisting of a symmetric filter and an anti-symmetric filter:

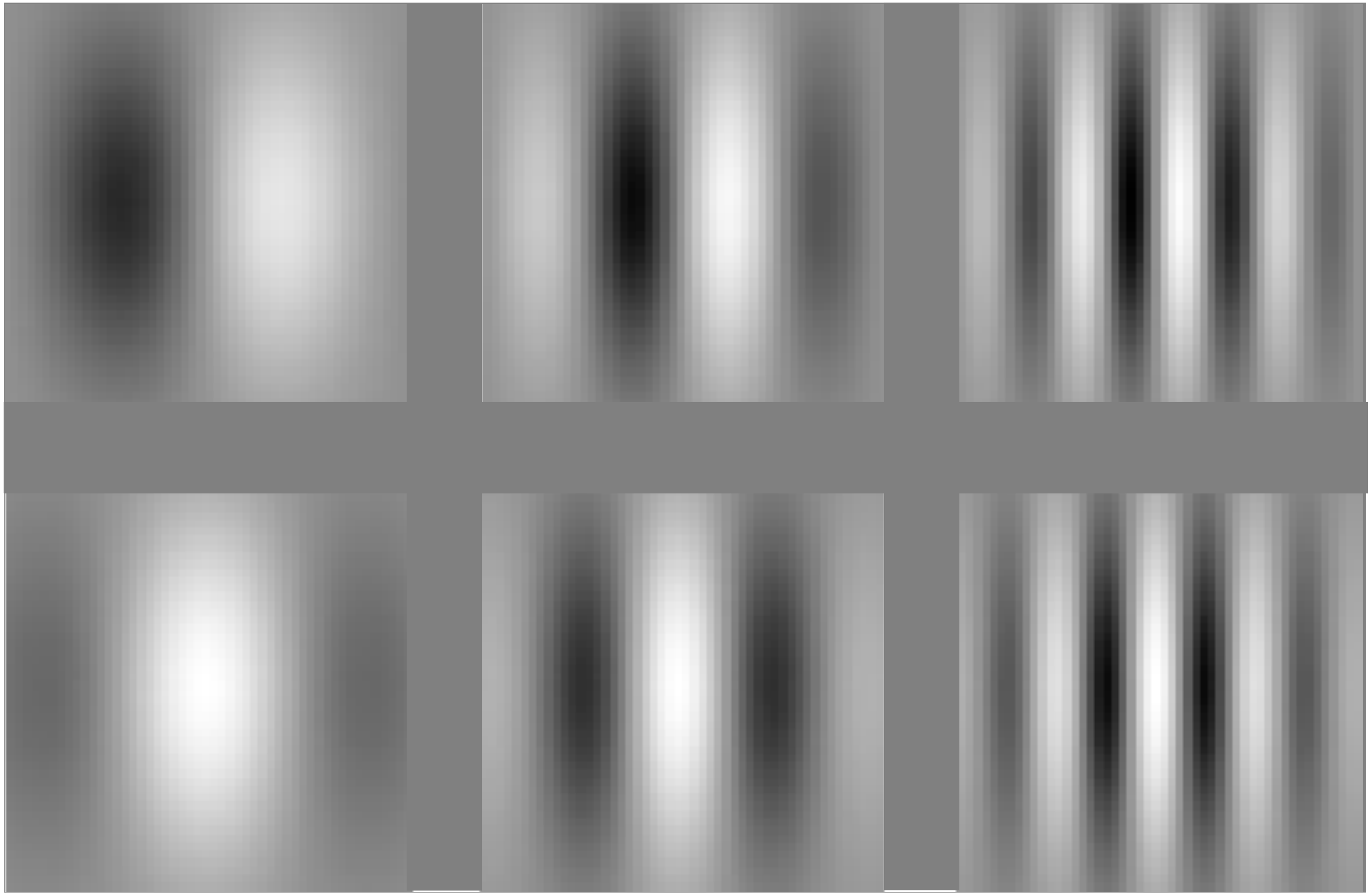
$$G_{\mathrm{sym}}(x,y) = \cos(k_x x + k_y y)\exp(-\frac{x^2+y^2}{2\sigma^2})$$

$$G_{\mathrm{asym}}(x,y) = \sin(k_x x + k_y y)\exp(-\frac{x^2+y^2}{2\sigma^2})$$

where k_x and k_y determine the spatial frequency and the orientation of the filter and σ determines the scale.

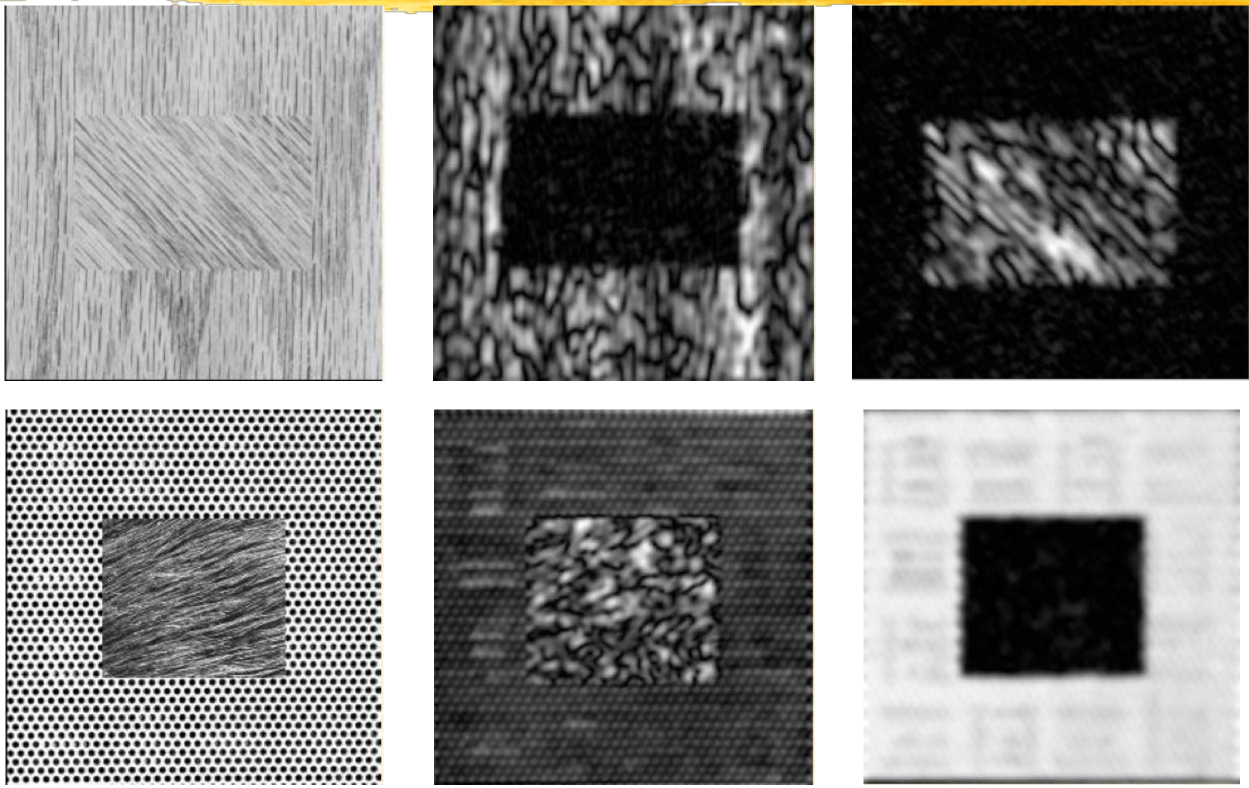
→ A filter bank is formed by varying the frequency, the scale, and the filter orientation

GABOR FILTERS

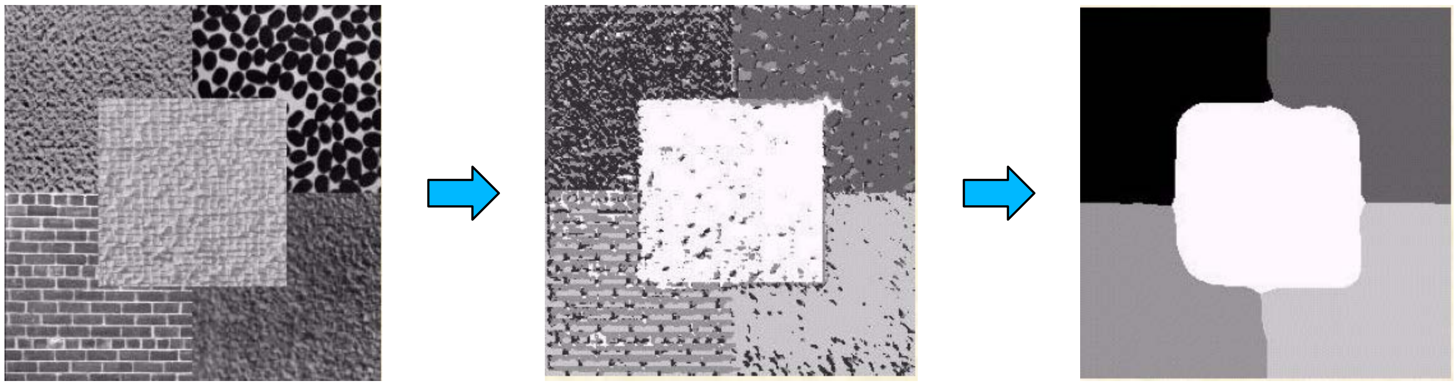


GABOR RESPONSES

Responses:



Segmentation:



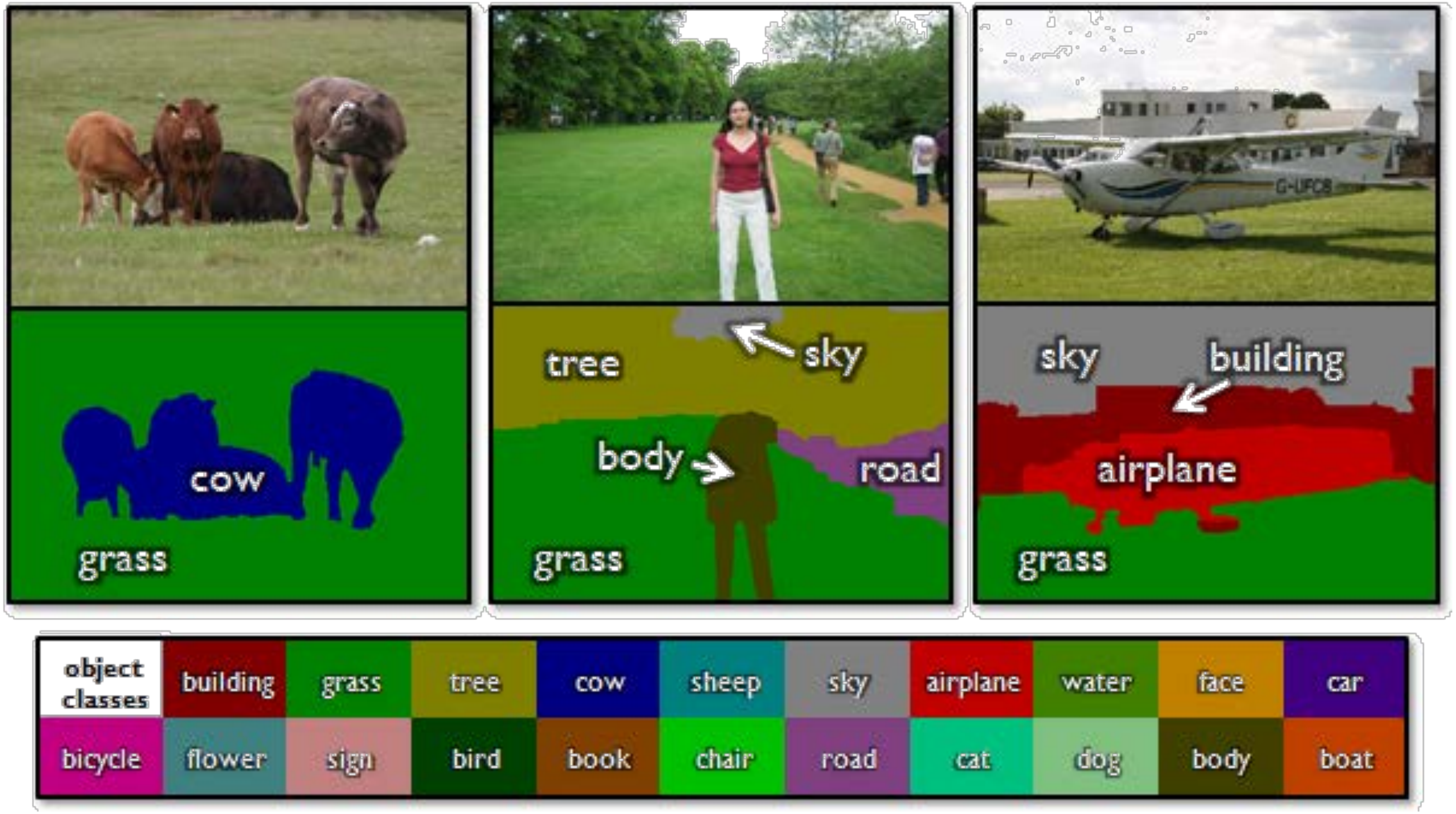
GABOR FILTER CHARACTERISTICS

- Respond strongly at points in an image where there are components that locally have a particular spatial frequency and orientation.

- In theory, by applying a very large number of Gabor filters at different scales, orientations and spatial frequencies, one can analyze an image into a detailed local description.

- In practice, it is not known how many filters, at what scale, frequencies, and orientations, to use. This tends to be application dependent and can be estimated using Machine Learning techniques.

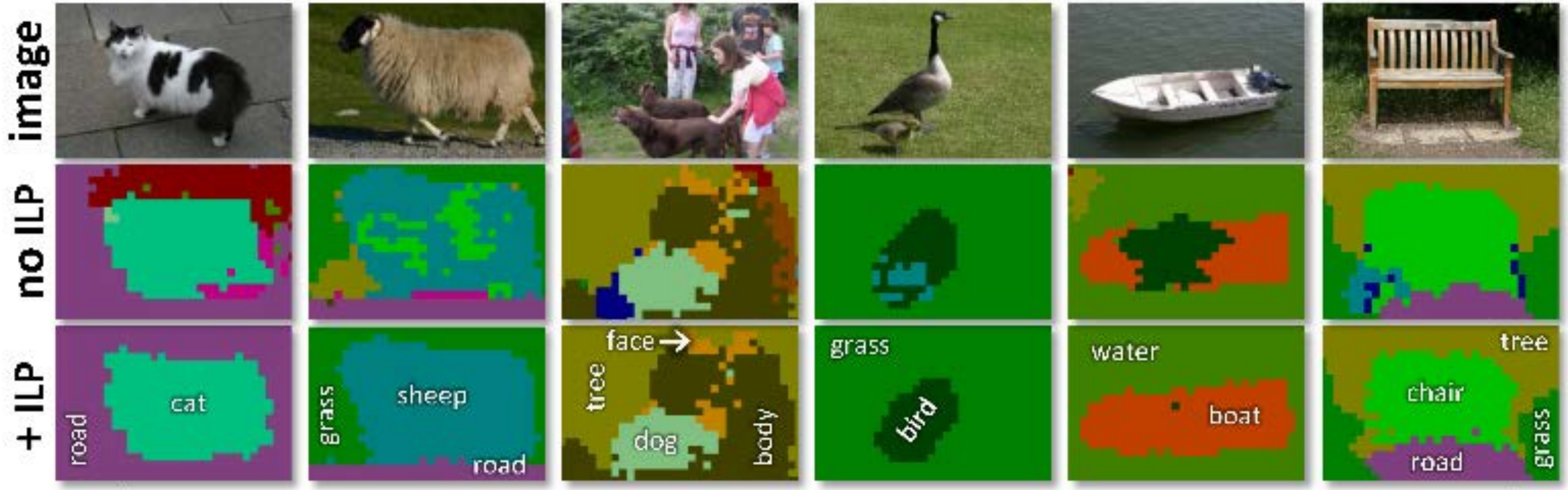
TEXTON BOOST



Performs classification on the output of oriented filters.

Shotton et al., ECCV'06

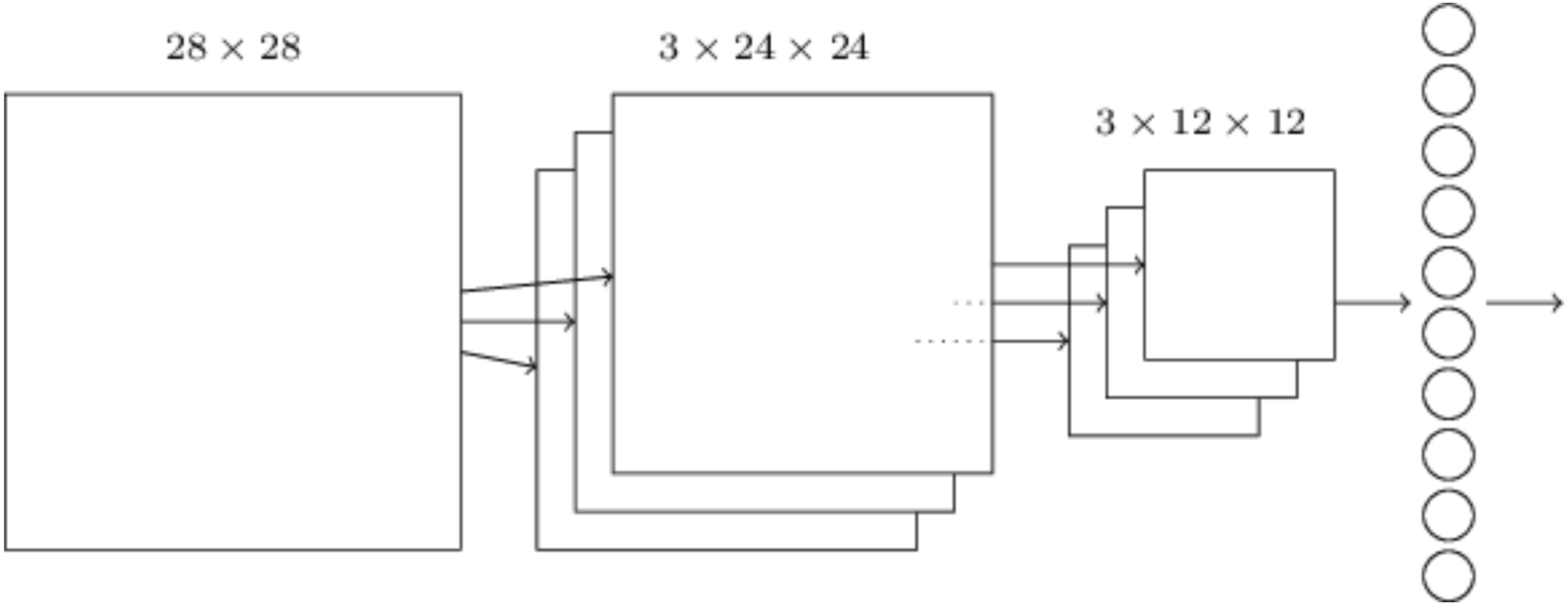
TEXTON FORESTS



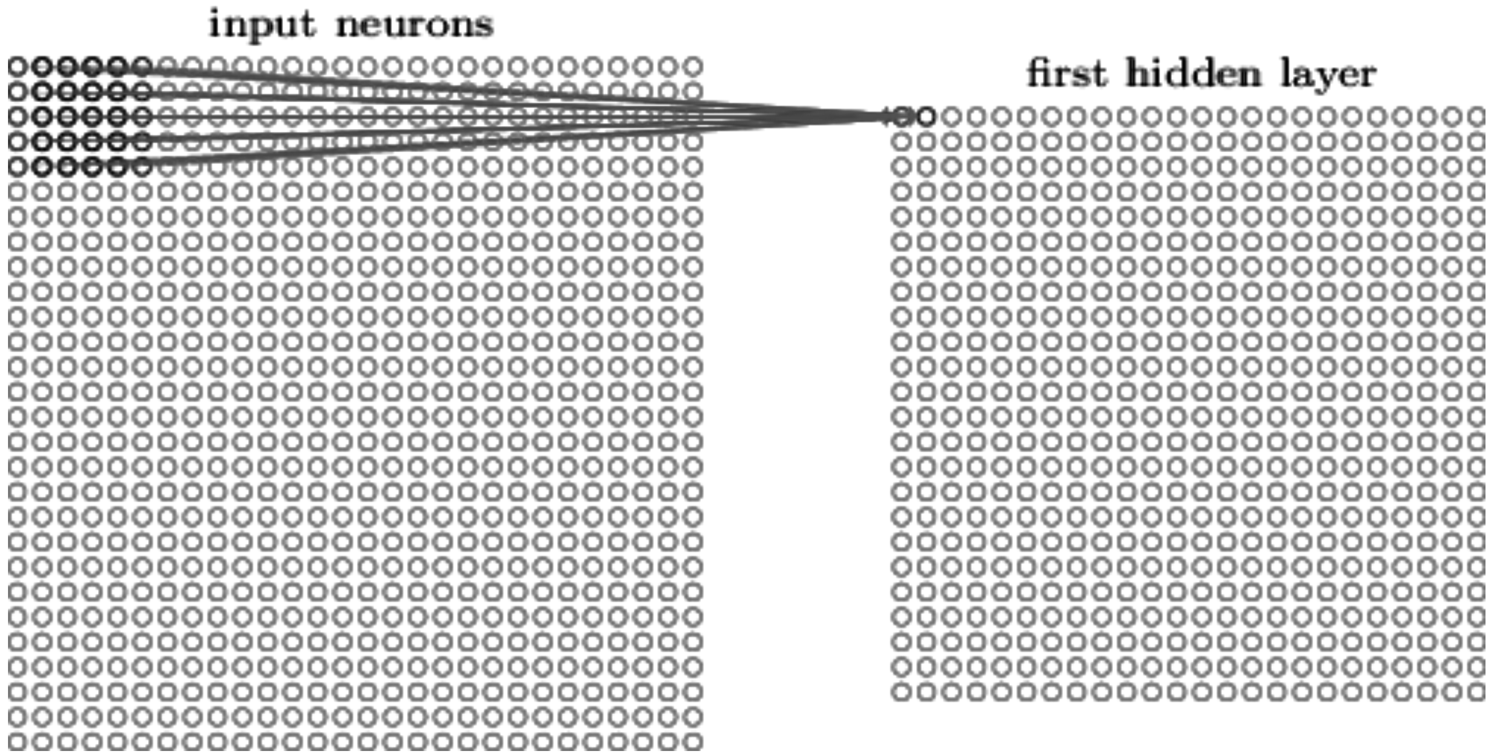
Relies on decision trees and comparisons of colors of pixels belonging to small image patches.

Shotton et al., CVPR'08

BACK TO CONVOLUTIONAL NETS

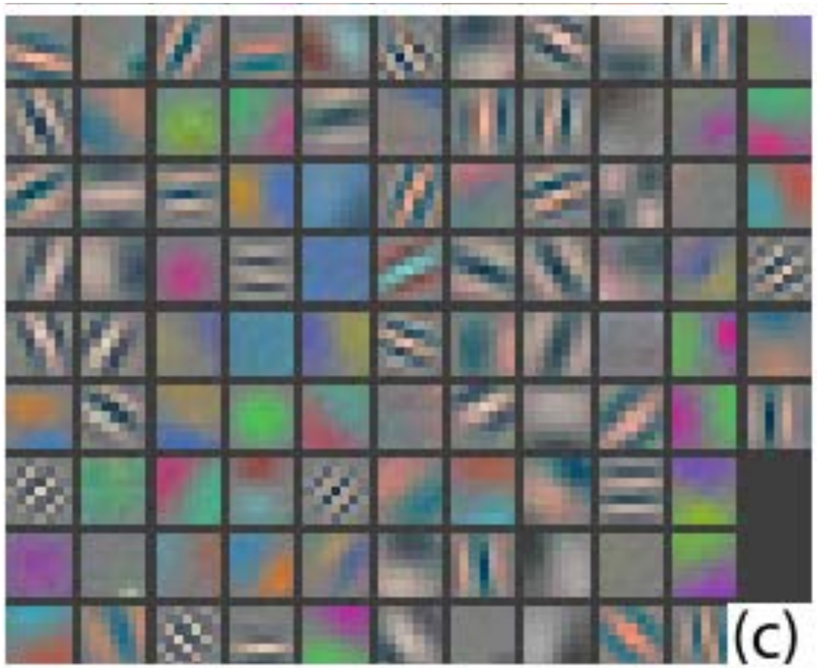


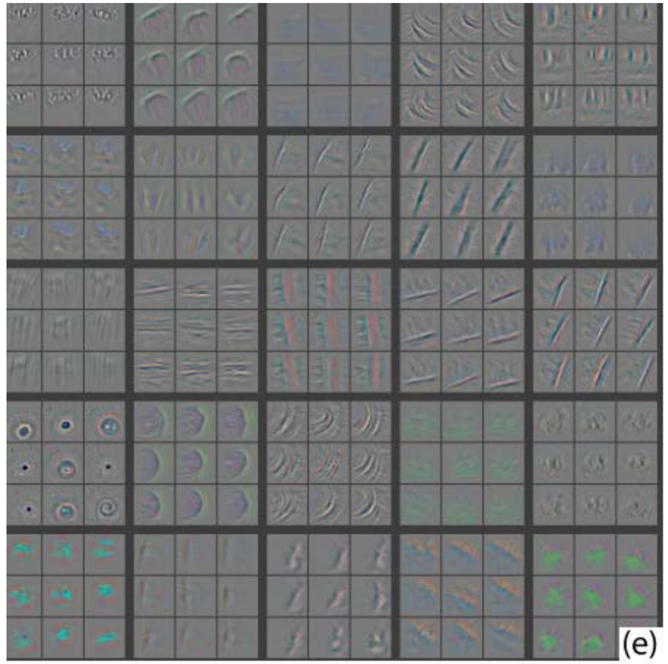
CONVOLUTIONAL LAYER



$$\sigma\left(b + \sum_{x=0}^{n_x} \sum_{y=0}^{n_y} w_{i,j} a_{i+x,j+y}\right)$$

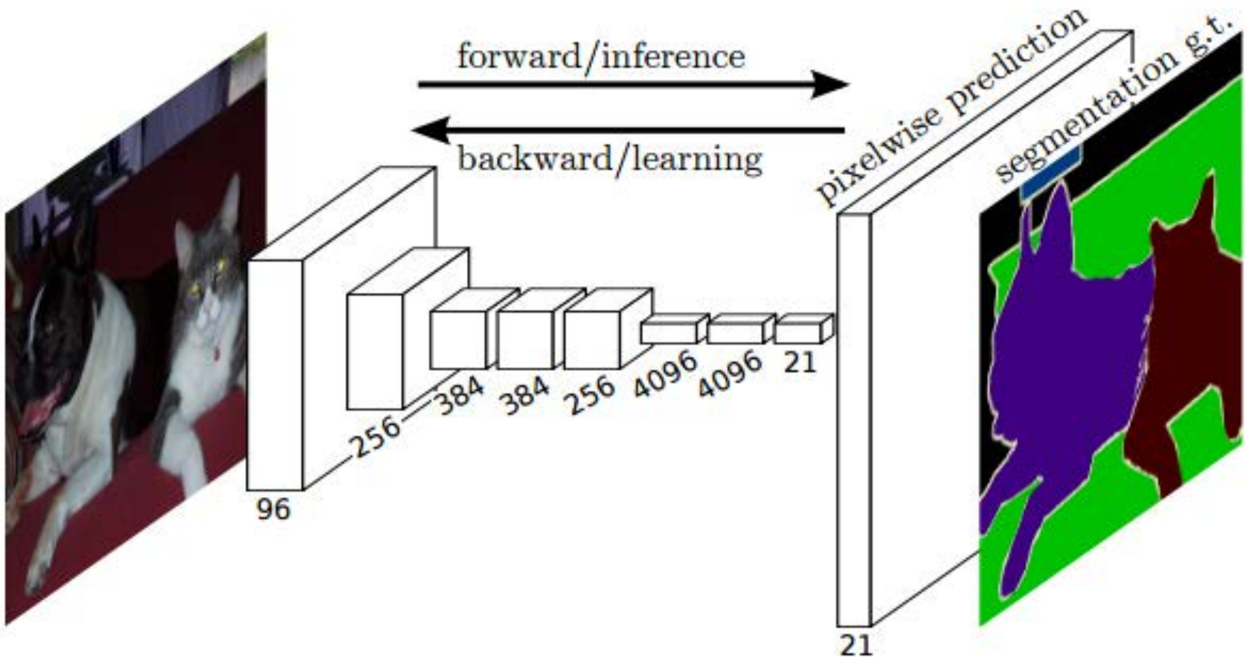
FEATURE MAPS





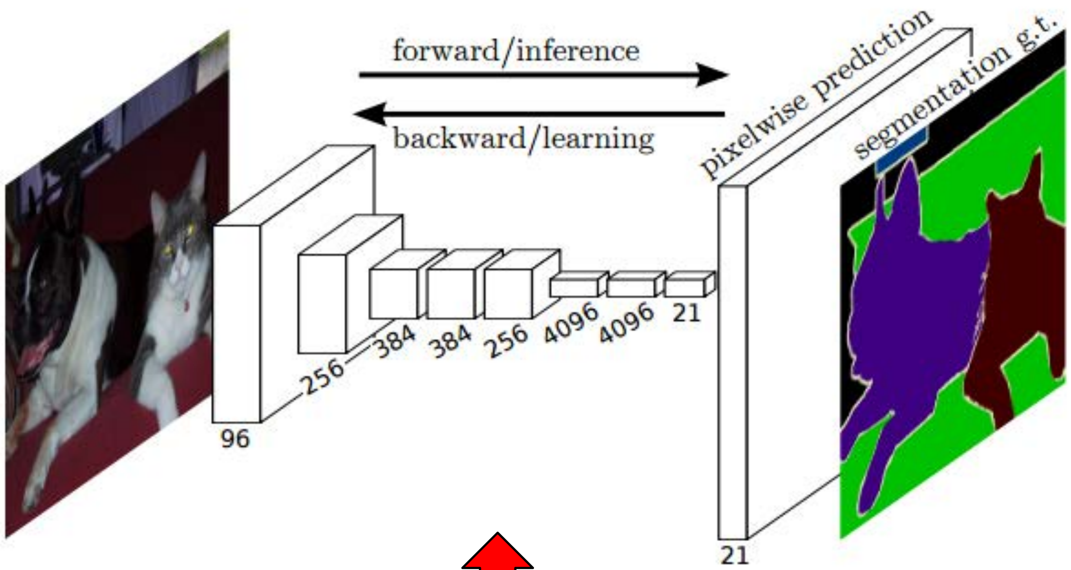
- Some of these convolutional filters look very Gabor like.
- The network learns the right filter bank but still depends on many arbitrary parameters.

CONVOLUTIONAL NETS

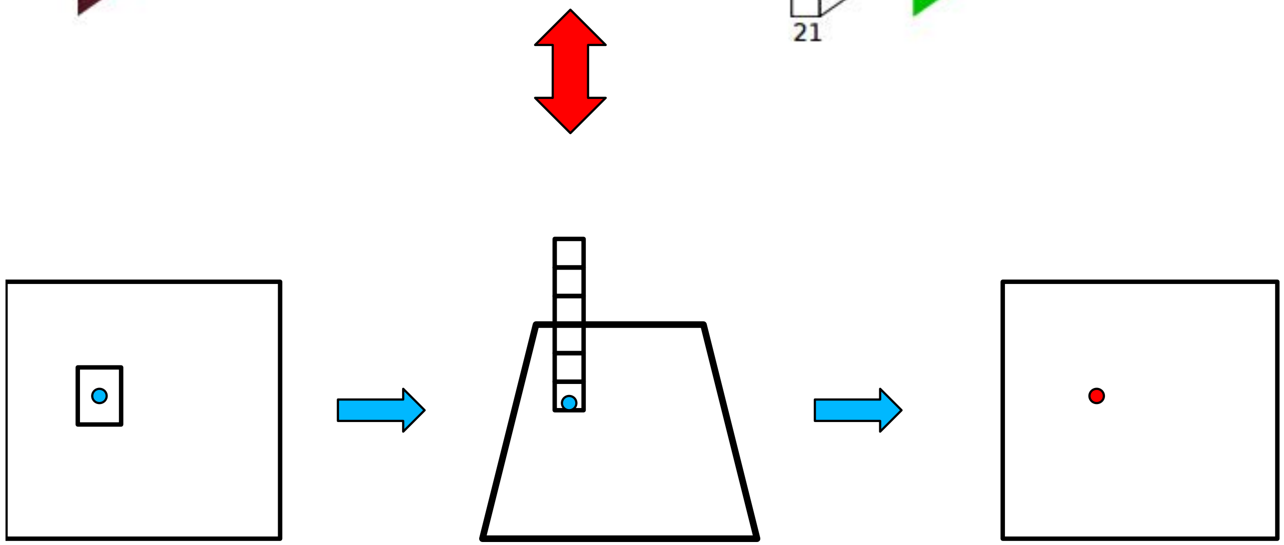


- Connect input layer to output one made of segmentation labels.
- Need layers that both downscale and upscale.
- Connect the lower layers directly to the upper ones.

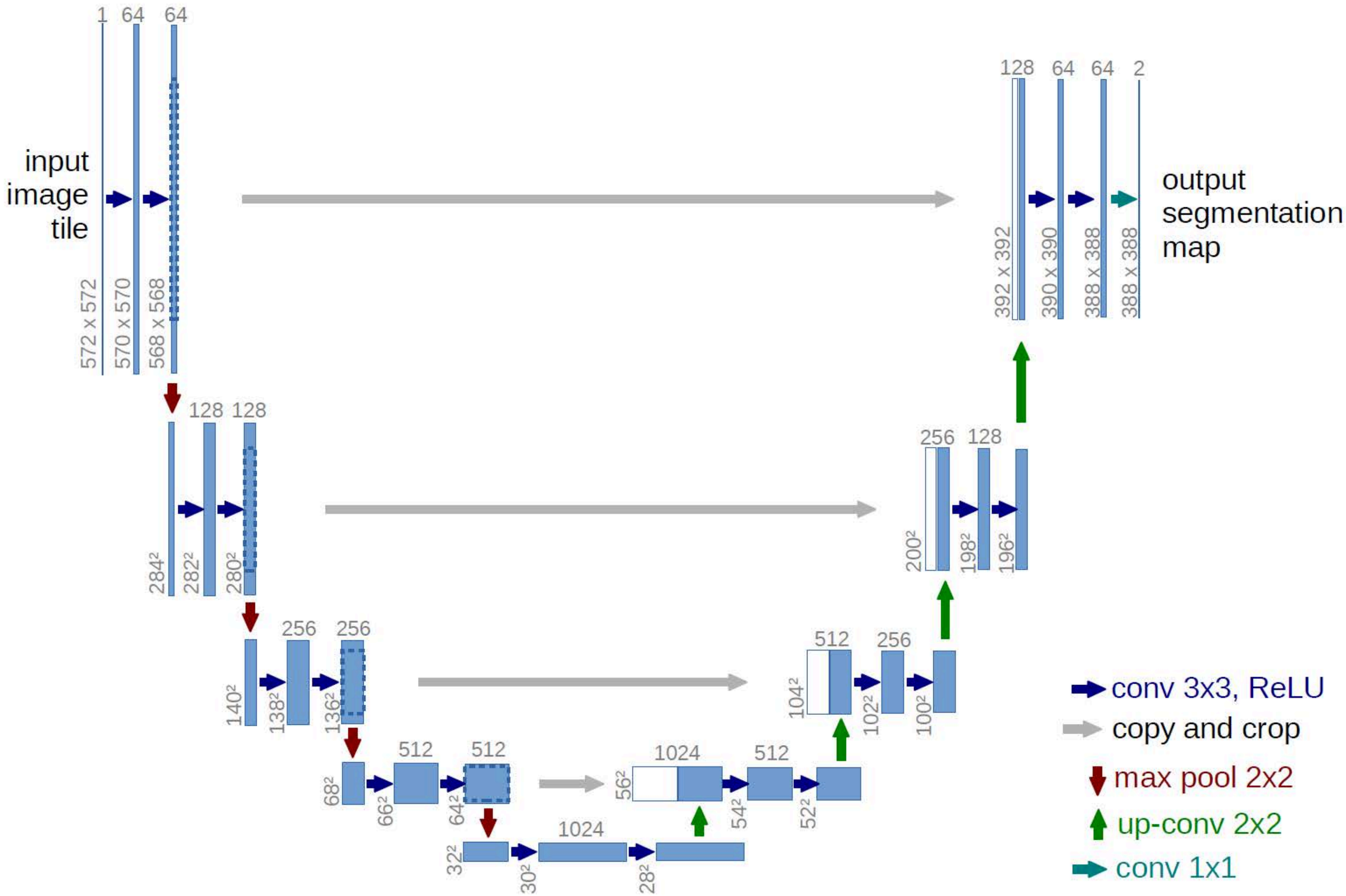
AN INTERPRETATION



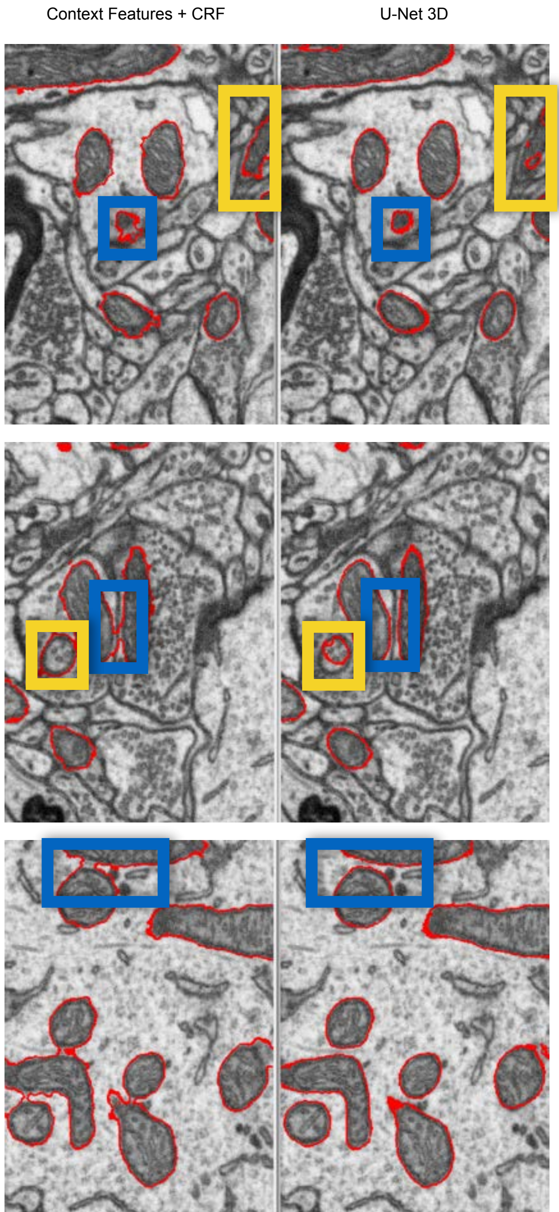
- Can be understood as generating for every output pixel a feature vector containing the output of all the intermediate layers.



U-NET ARCHITECTURE

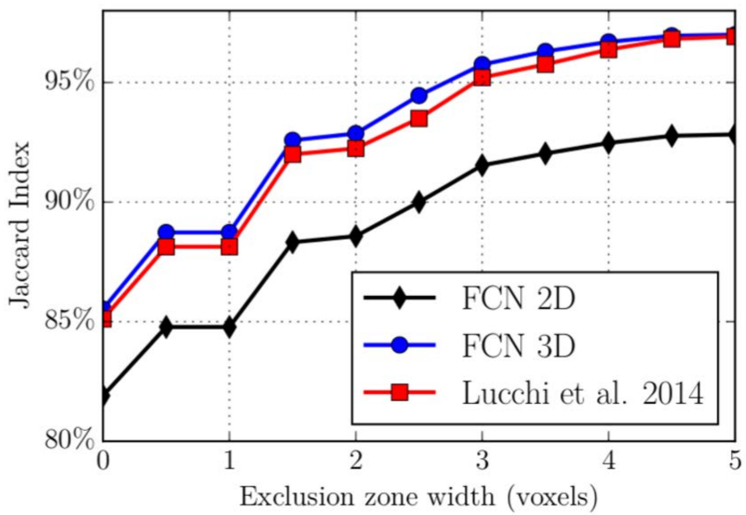


FROM GRAPH CUT TO U-NET



Striatum Mitochondria

Method	Jaccard Index
Context F. + CRF	84.6%
U-Net 2D	82.4%
U-Net 3D	86.1%



IN SHORT

Texture is a key property of objects which is

- Non local
- Non trivial to measure
- Subject to deformations

➡ Hard to characterize formally and best used in conjunction with effective Machine Learning techniques.

➡ This may be exactly what Convolutional Neural Nets do.