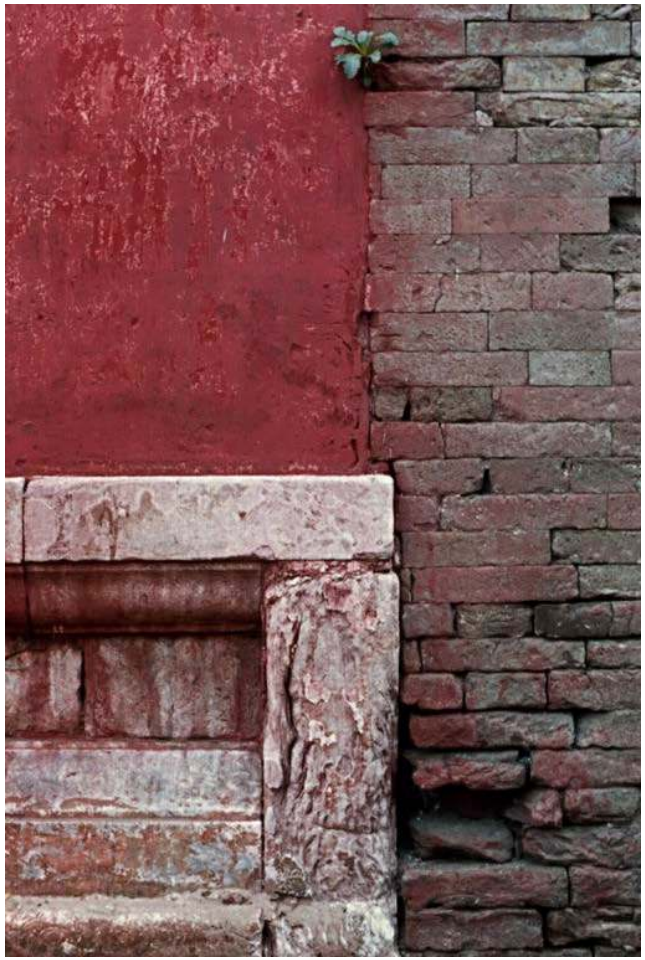
Texture

↘ Local statistics of the image

- What is texture?
- Texture analysis
- Deep Texture



Reminder: Homogeneous or Not?

What does it mean?

in some sense

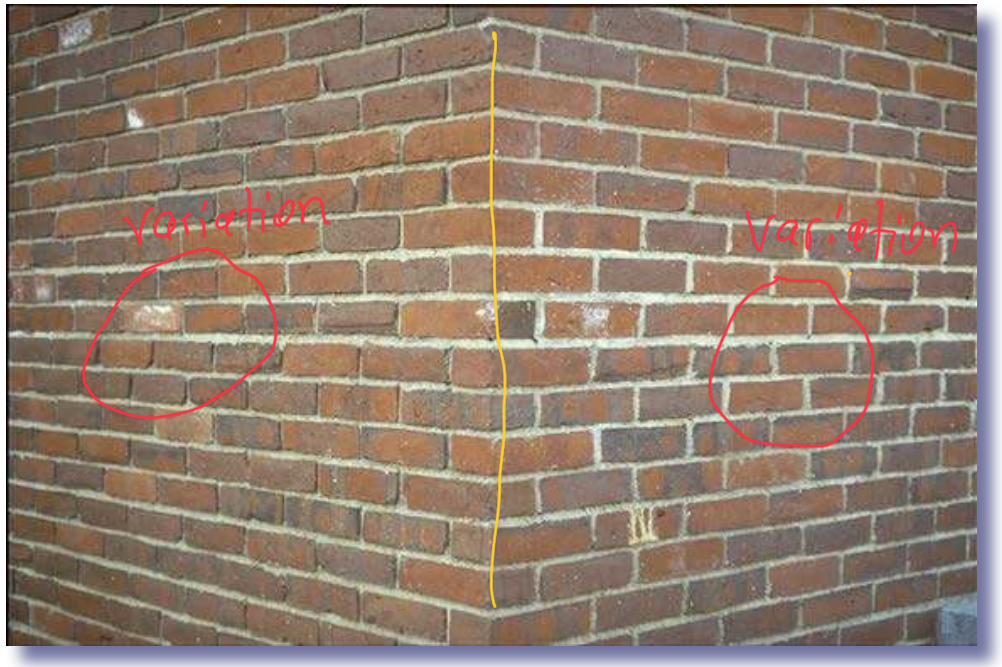
What is homogeneous in some parts of these images are the shared statistical properties, not the actual pixel values.

Texture-Based Segmentation

Ideally, we would like to:

- 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-Based Edges



Similarly, we would like to be able to find boundaries between textures.

What is Texture?

no legal shape

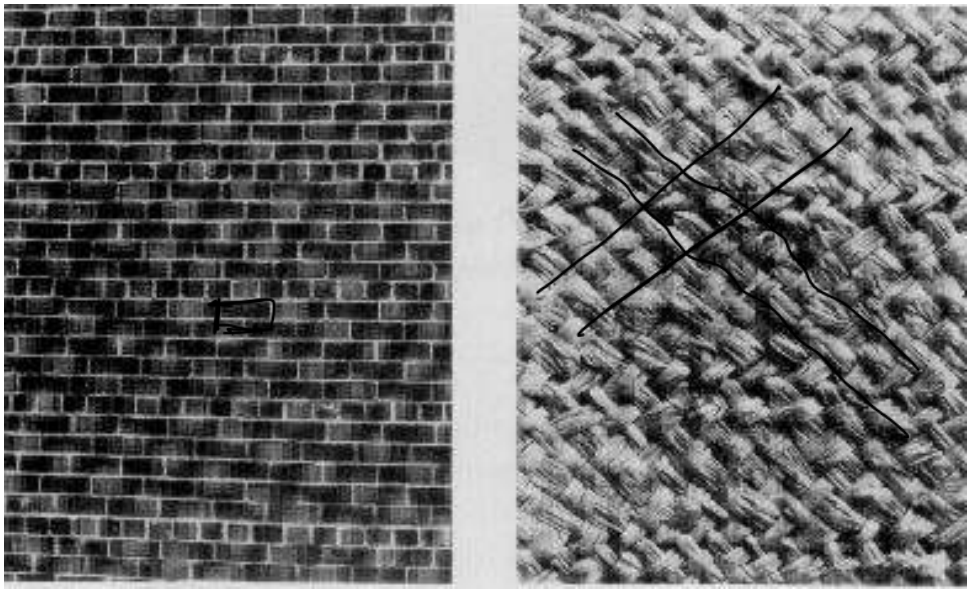
Repetition of a basic pattern:

- Structural ← geometry pattern that repeats
- Statistical ← reasonably similar across whole img statistically (constant density)

→ Non local property, subject to distortions.

texture does not ⊥ pixels

Structural Textures



e.g. windows → texels
not buildings

Repetitive Texture Elements (Texels)

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

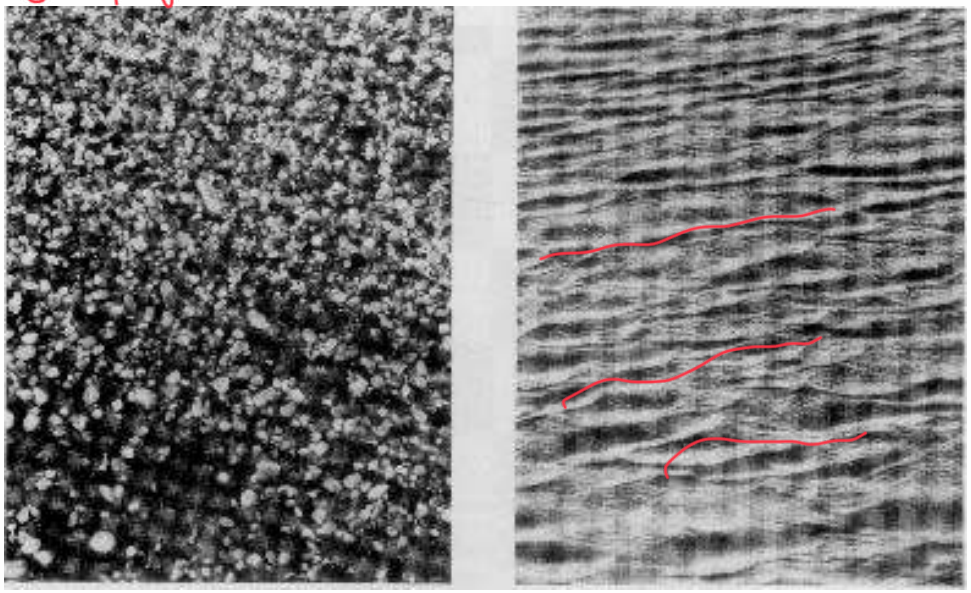
Statistical Textures

statistical property that repeats

→ constant density of pebbled →

waves → constant distance between

→ statistically consistent orange, black stripes → repetitive



no geometric pattern

Homogeneous Statistical Properties

Textured vs Smooth

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

more or less uniform

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

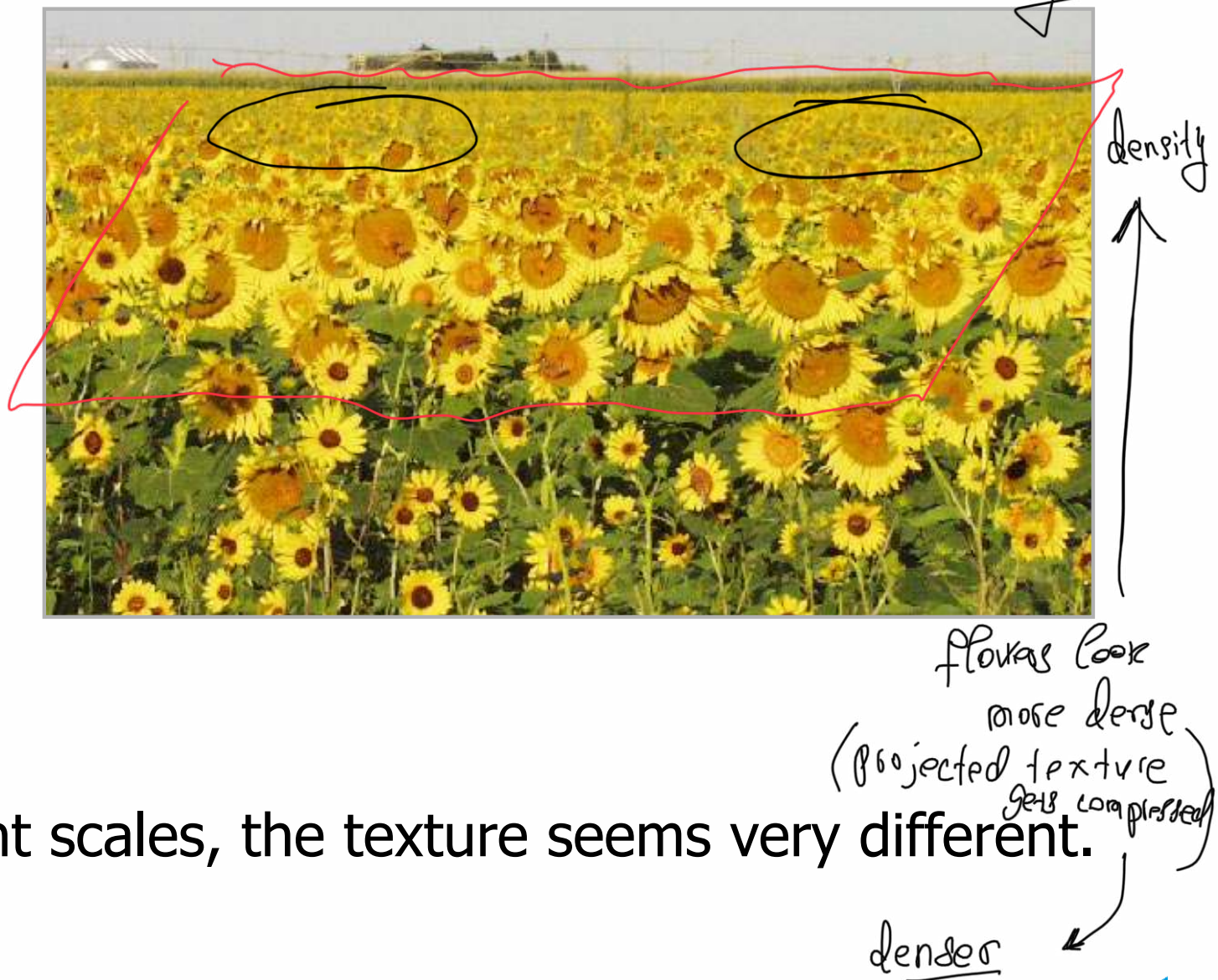
(e.g. table → smooth)

(in microscopic scale, it incredibly looks rough

You don't see relief

→ Texture is a scale dependent phenomenon

Scale Dependence



At these two different scales, the texture seems very different.

Structural vs Statistical

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

What are the fundamental texture primitives in this image? elements?

- Numeric quantities or statistics that describe a texture can be computed from the gray levels or colors alone. (easier to implement)

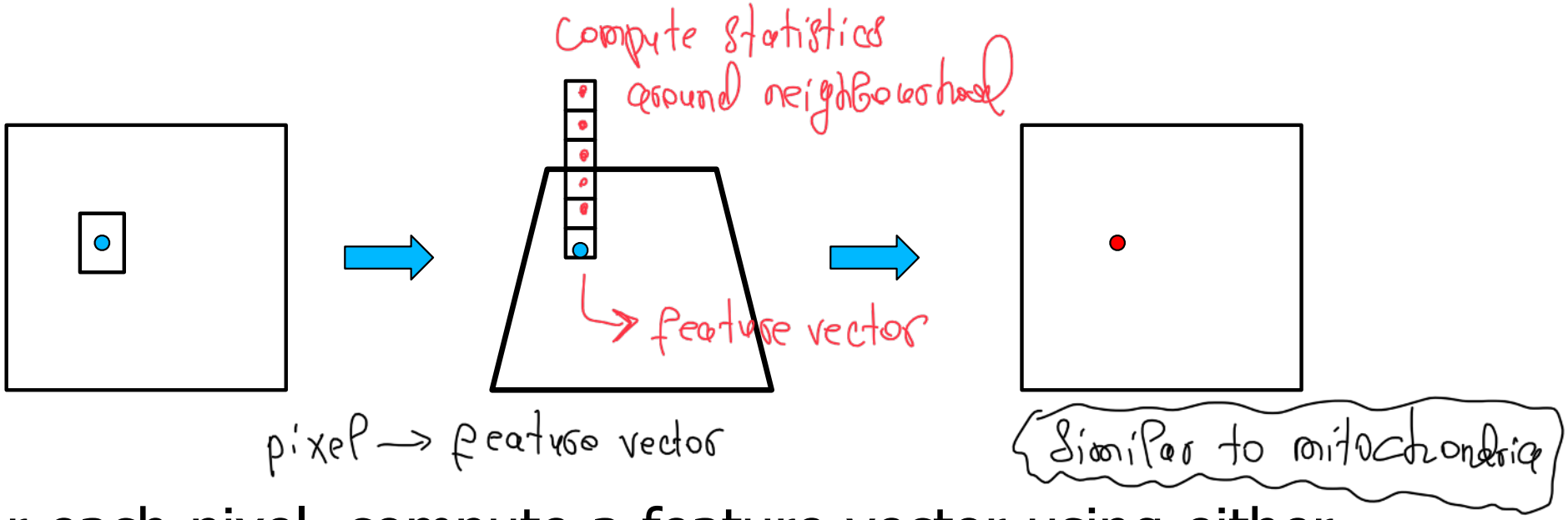
image

→ The statistical approach is less intuitive, but more effective in practice.

Creating Textural Images

There is no such thing of statistics of the pixel

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

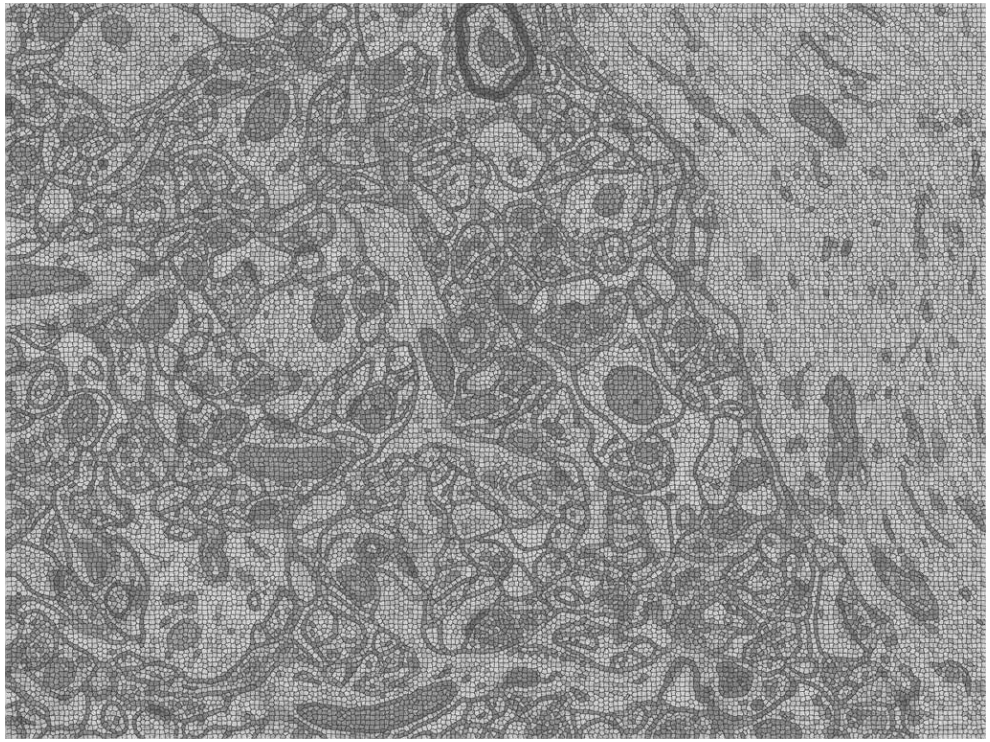


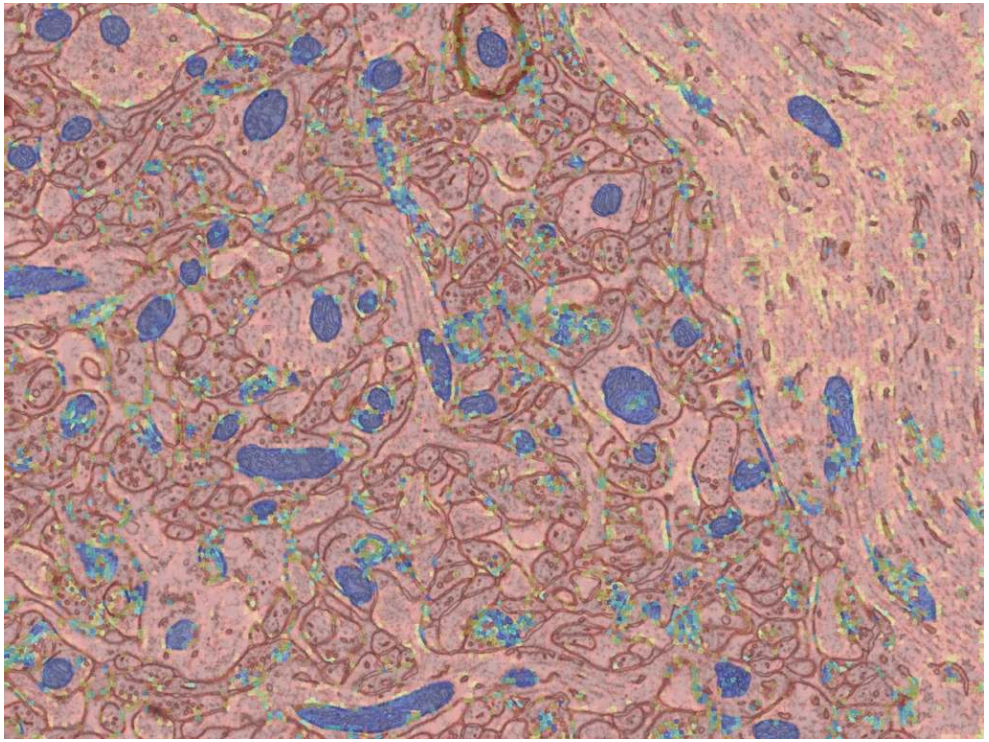
- For each pixel, compute a feature vector using either an image patch or a set of filters.

Convolving img patches

- Run a classification algorithm to assign a texture value to each pixel.

Reminder: Mitochondria





- Compute image statistics for each superpixel.
- Train a classifier to assign a probability to be within a mitochondria.

to each superpixel

—> We used the super pixels to compute local statistics.

Textural Metrics

Spectral metrics:

- Texture is characterized by the properties of its Fourier transform.

Statistical Metrics:

- Texture is as statistical property of the pixels' intensity and color in a region. wrt each other

Deep Net Metrics:

- They have now mostly superseded the others.
- They encompass the earlier concepts.

Superset of the first 2

Reminder: Discrete Fourier Transform

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

image f

sum of weighted complex exponentials

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

The DFT is the discrete equivalent of the 2D Fourier transform:

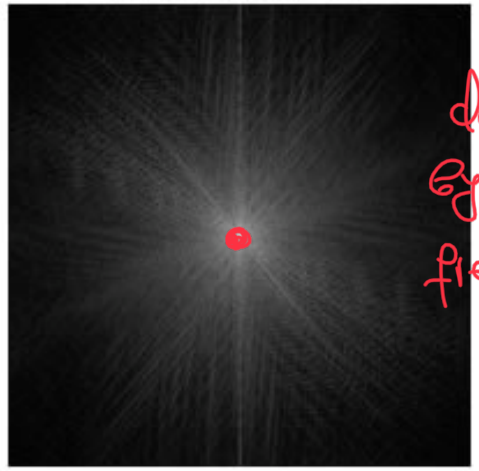
- The 2D function f is written as a sum of sinusoids.
- The DFT of f convolved with g is the product of their DFTs.

Spectral Analysis

F → complex number

Sheep

DFT Modulus



dominated by low frequencies

y

x

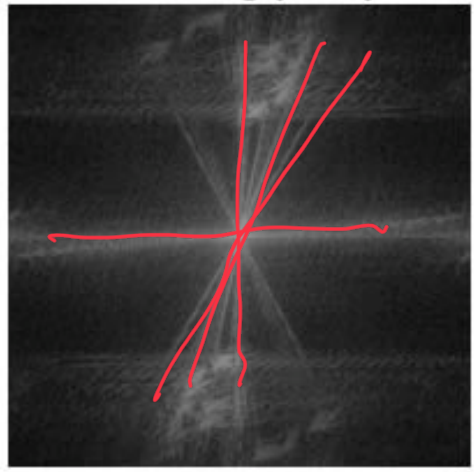
v

u

Lines in the DFT modulus images capture the main orientations in the image.

Building

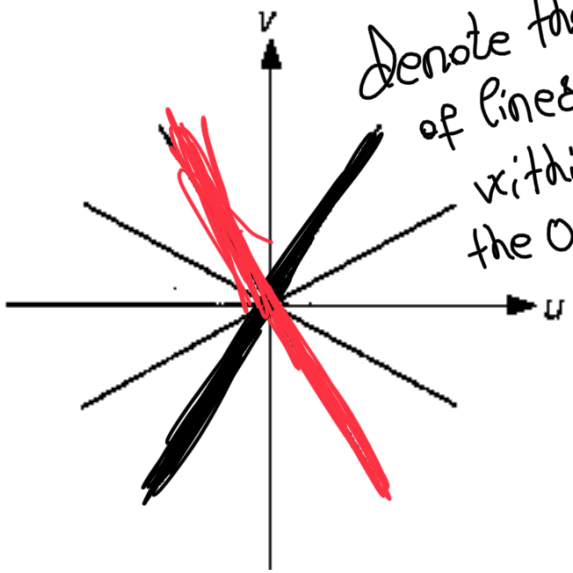
DFT Modulus



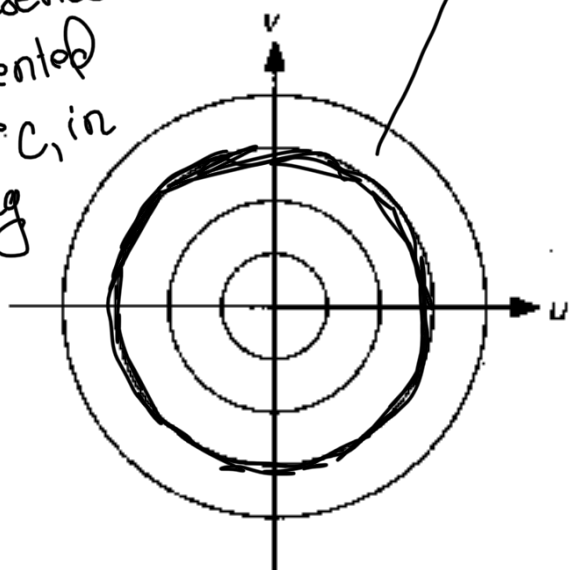
lines in various directions

corresponds (generates)

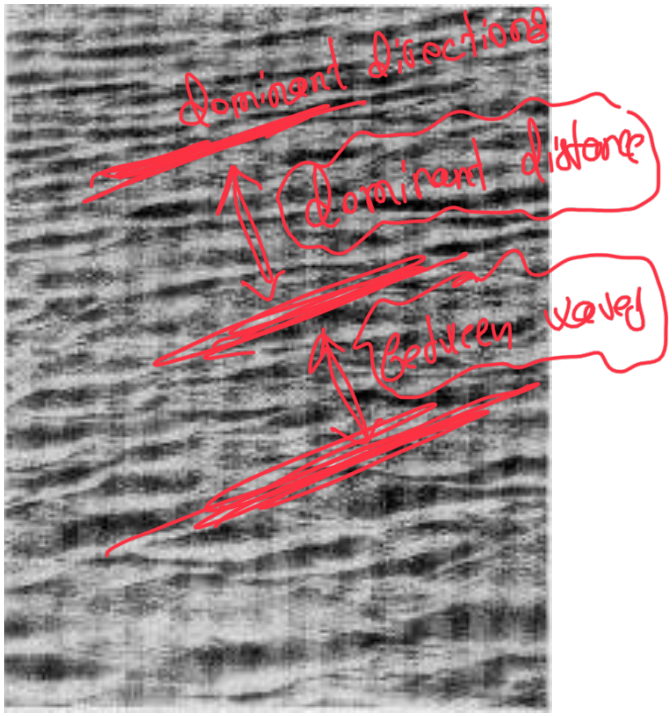
Texture Analysis



Angular bins
in |DFT| image

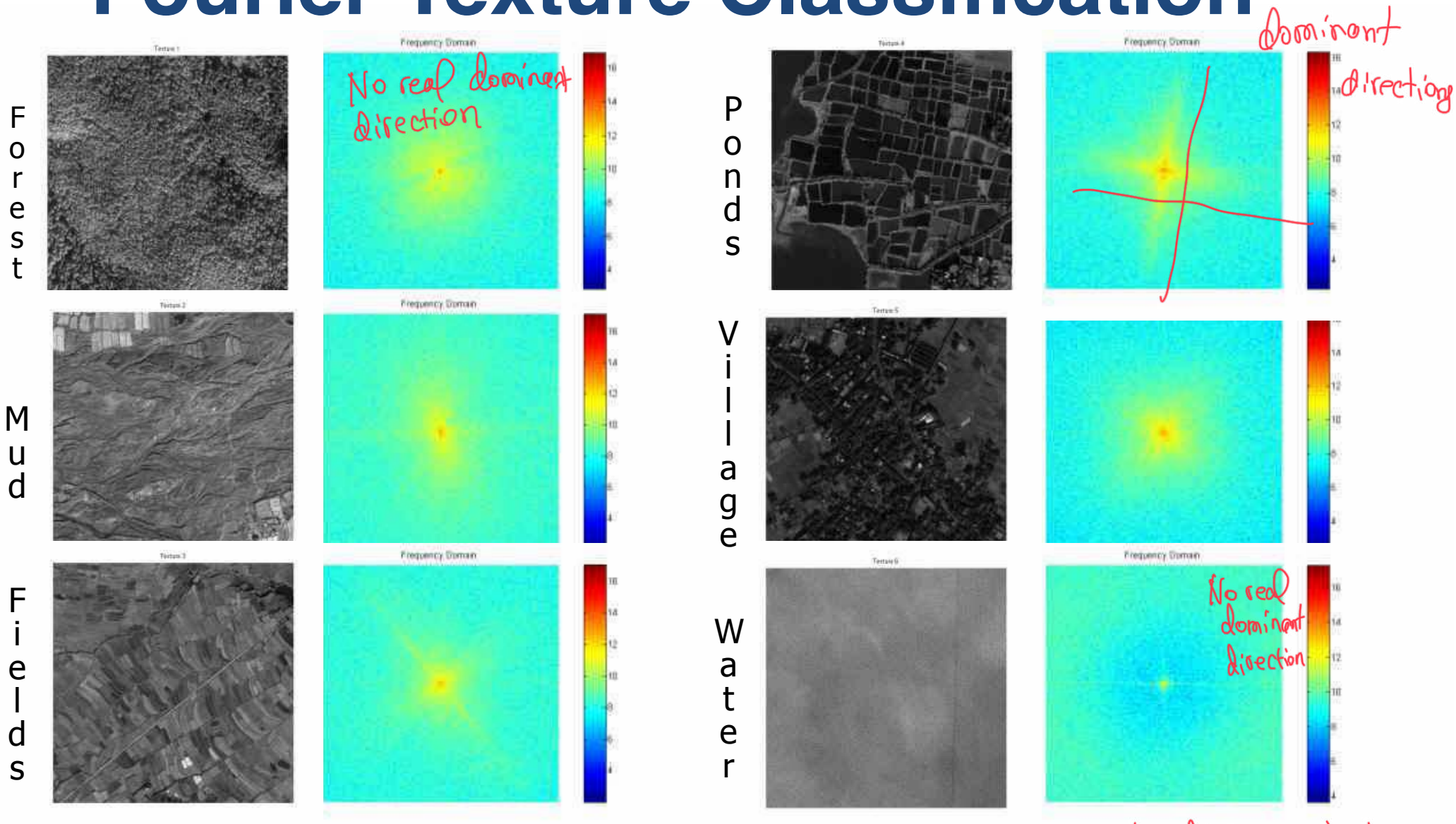


Radial bins
in |DFT| image



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

Fourier Texture Classification



- For some types of textures, the Fourier spectra are easily distinguishable.
- A classifier can be trained to tell them appart.
- However, one must have the same texture in the whole image patch.

Limitations

- DFT on small patches is subject to severe boundary effects.
- Only applicable if texture is uniform over large areas.
- Results can be improved by using wavelets instead, but only up to a point.

—> More local metrics for segmentation are required.

Statistical Metrics

First order gray-level statistics:

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

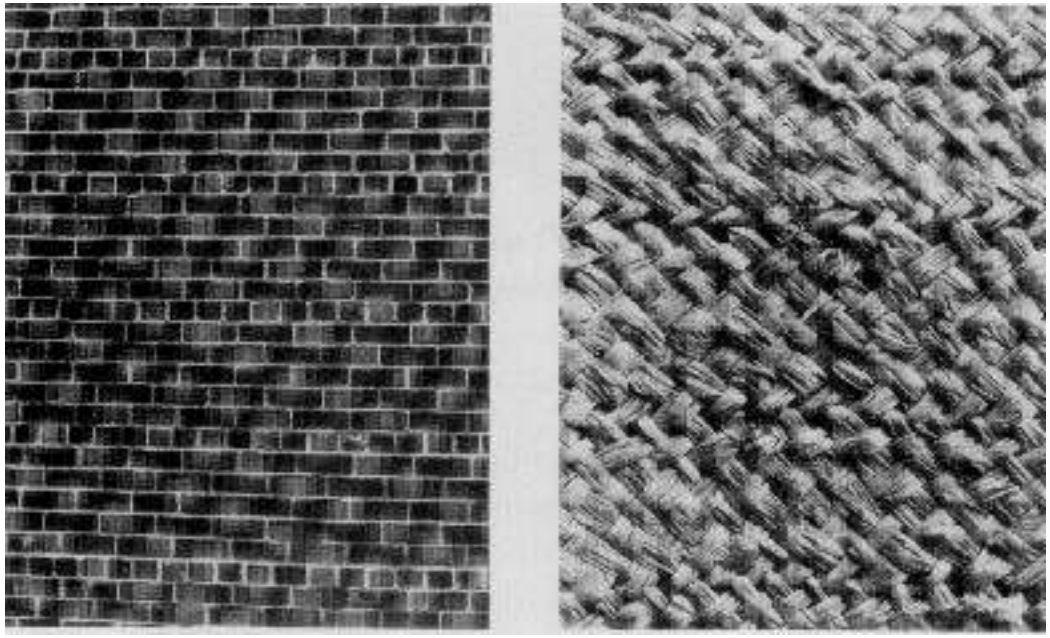
Second order gray-level statistics:

- Statistics of pixel pairs.

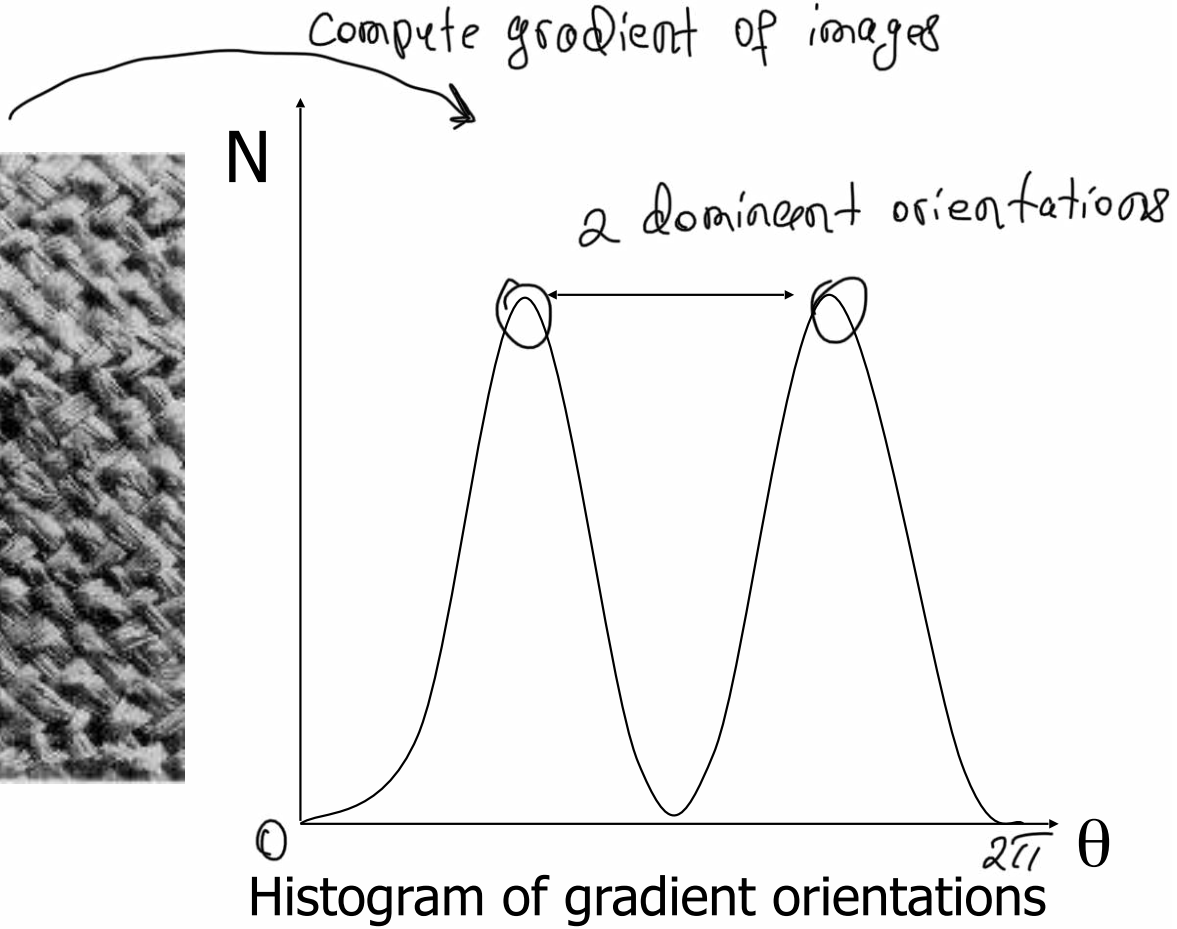
Filter-based measures:

- Statistics of whole neighborhoods.

Simple First Order Measure



How to recognize texture?



Histogram of gradient orientations

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

recognizable

→ not incredibly generic

More First Order Measures

Edge Density and Direction: Histogram of intensities

- 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

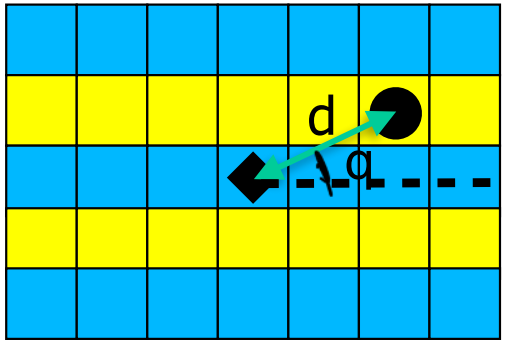
Edgeness per unit area: How sharp or pronounced the edges in a texture are

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

Edge magnitude and direction histograms:

- { H_G, H_t}

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

(i) (j)
→ of a transition from one gray-level to another

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

Simple Example

small images coded $0,1,2,3 \rightarrow$ 2-bits

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

count

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

How many times i and j are neighbours

transition from gray level l to gray level m

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

1 pixel is immediate neighbour of the other one to the right

# of all possible pairs

Co-Occurrence Matrix

No need to distinguish between

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

transition

and

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

→ Co-Occurrence matrix C:

$$C = H + H^T$$

↑
marked C symmetric

Second Order Measures

Once you have matrix H, you can find

Contrast:

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

probability of this happening often

large for pixels whose colors are different

Maximized: for img where pixels are black or white

Minimized: uniform

Dissimilarity:

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

Homogeneity:

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

and many more .....

Angular Second Moment (Energy, Uniformity):

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

Entropy:

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

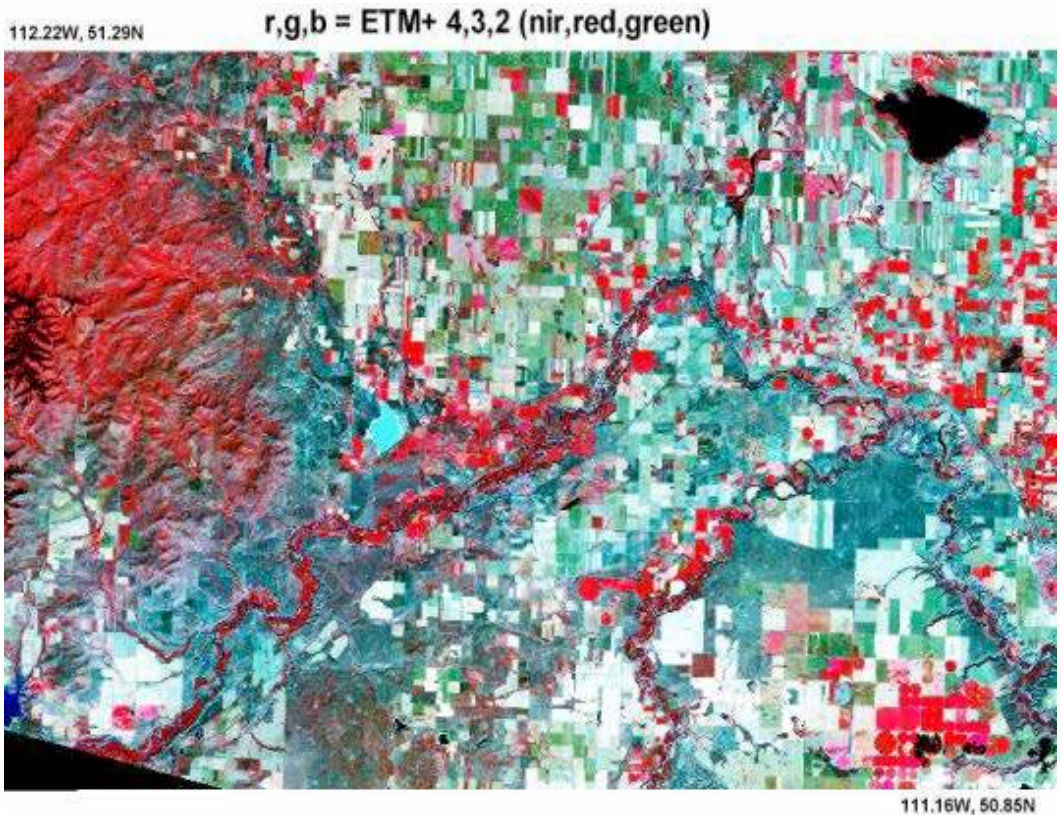
measure of disorder

- 2, 3 colors → entropy low
- multiple colors → entropy high with uniform presence

Landsat Image

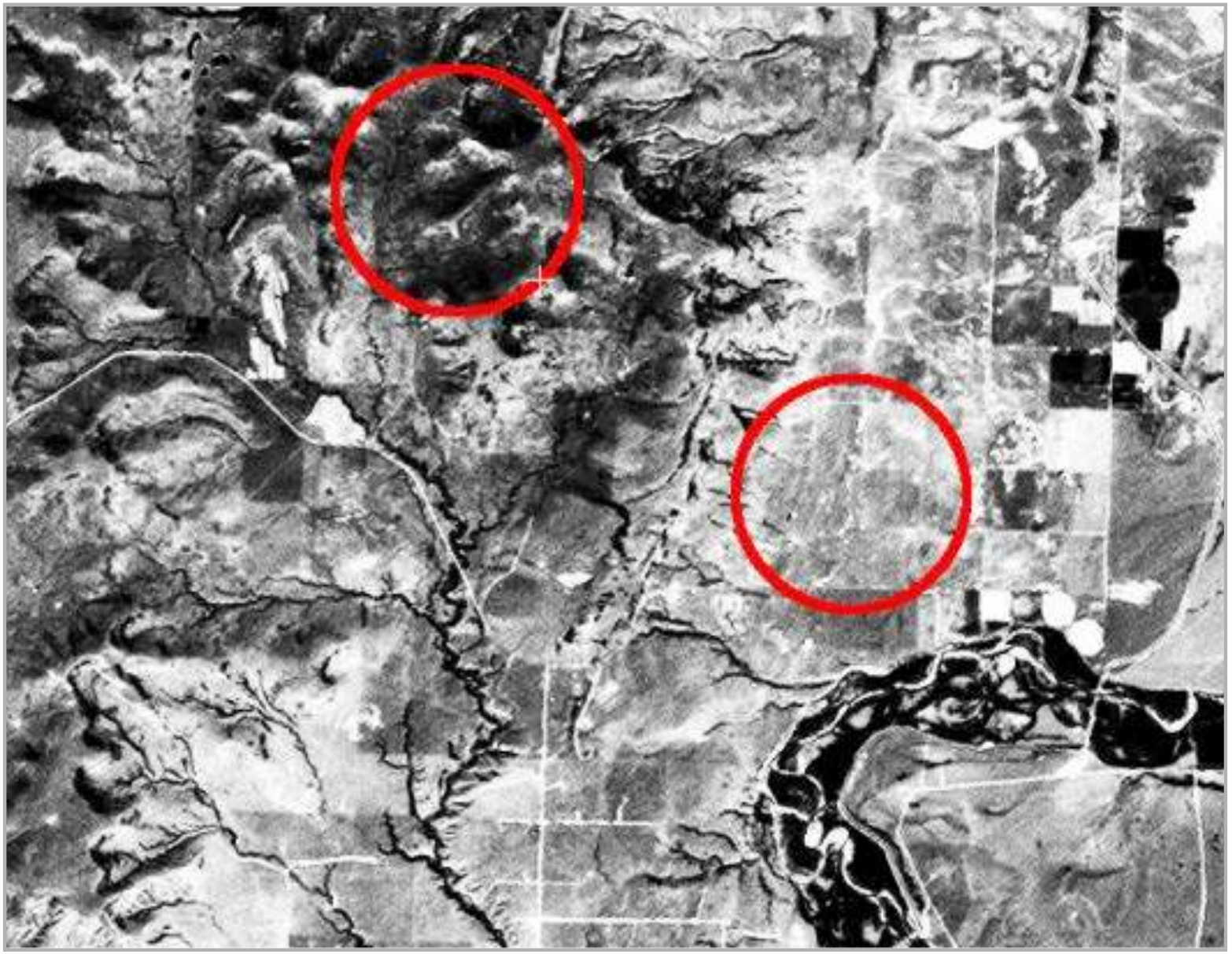
Aerial image

Classify ⇒ mountains
agriculture
urban
⋮



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.

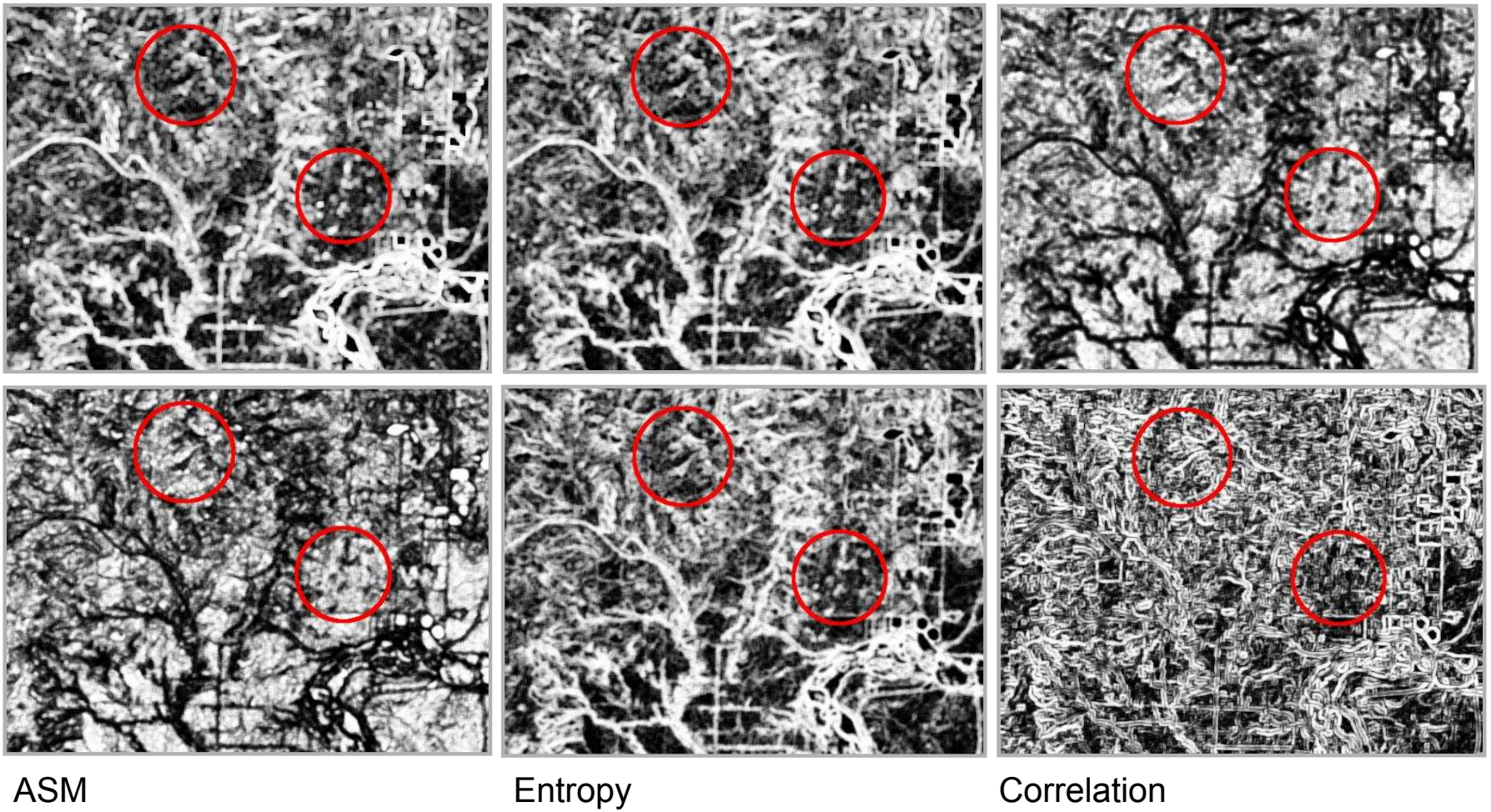
Full Resolution



Let us consider two areas, one in the hills, the other in the plain.

Compute second-order measures for those regions (co-occurrence matrices)

Using Second Order Measures



The various measures within the two areas are sufficiently different for a classifier to easily distinguish them.

Classification

Used to identify eight terrain classes:

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

Parameter Choices

Using co-occurence matrices requires choosing:

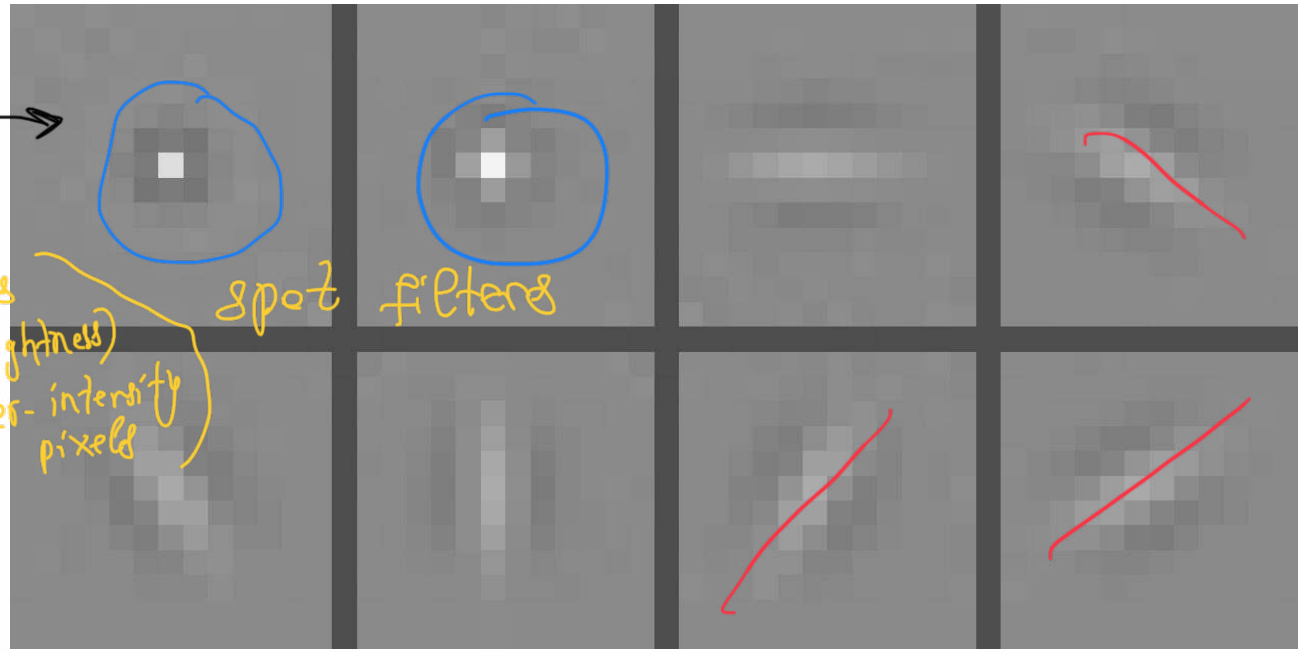
- window size, ⇝ during the matrix computation
- direction of offset,
- offset distance,
- what channels to use,
- what measures to use.

How do we choose these parameters?

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

with good validation set

Filter Based Measures

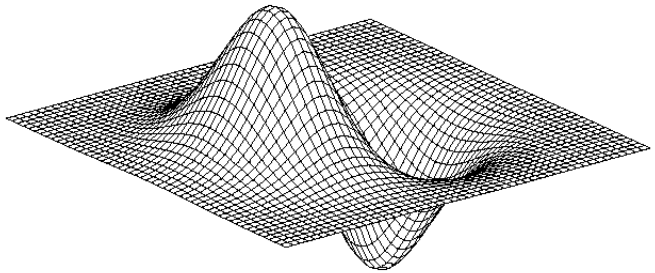


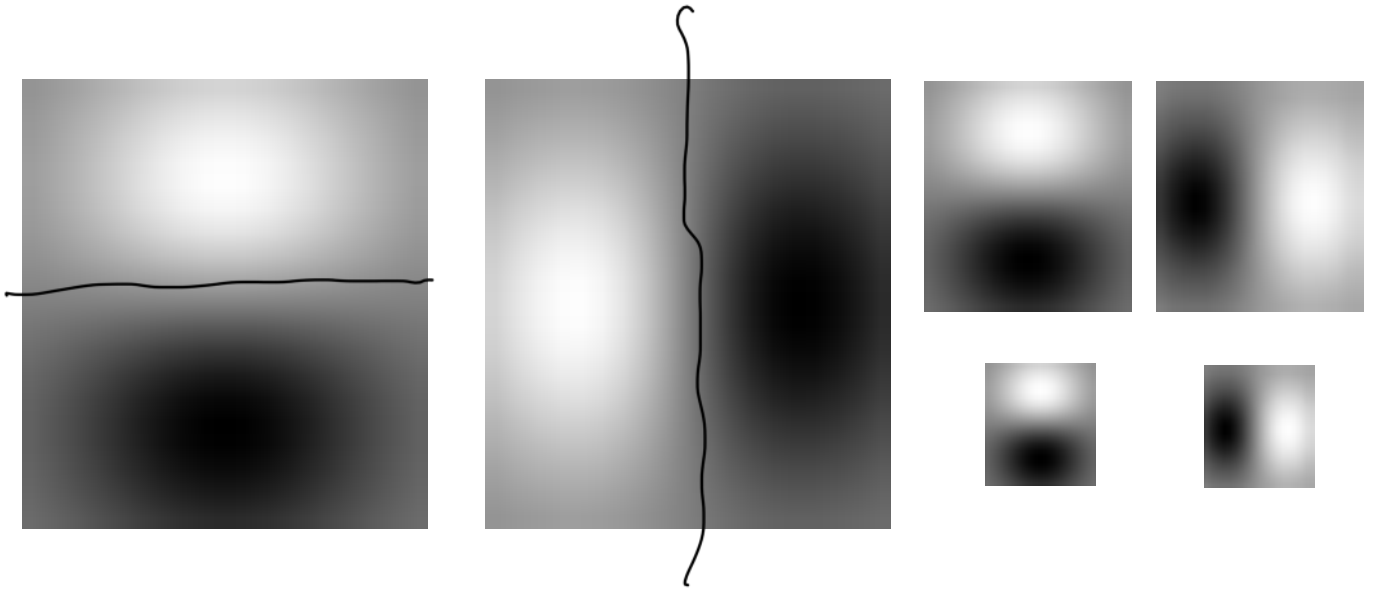
Represent image textures using the responses of a collection of filters. → convolve with block filters

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

Gaussian Filter Derivatives

(similar to what we did for edges)



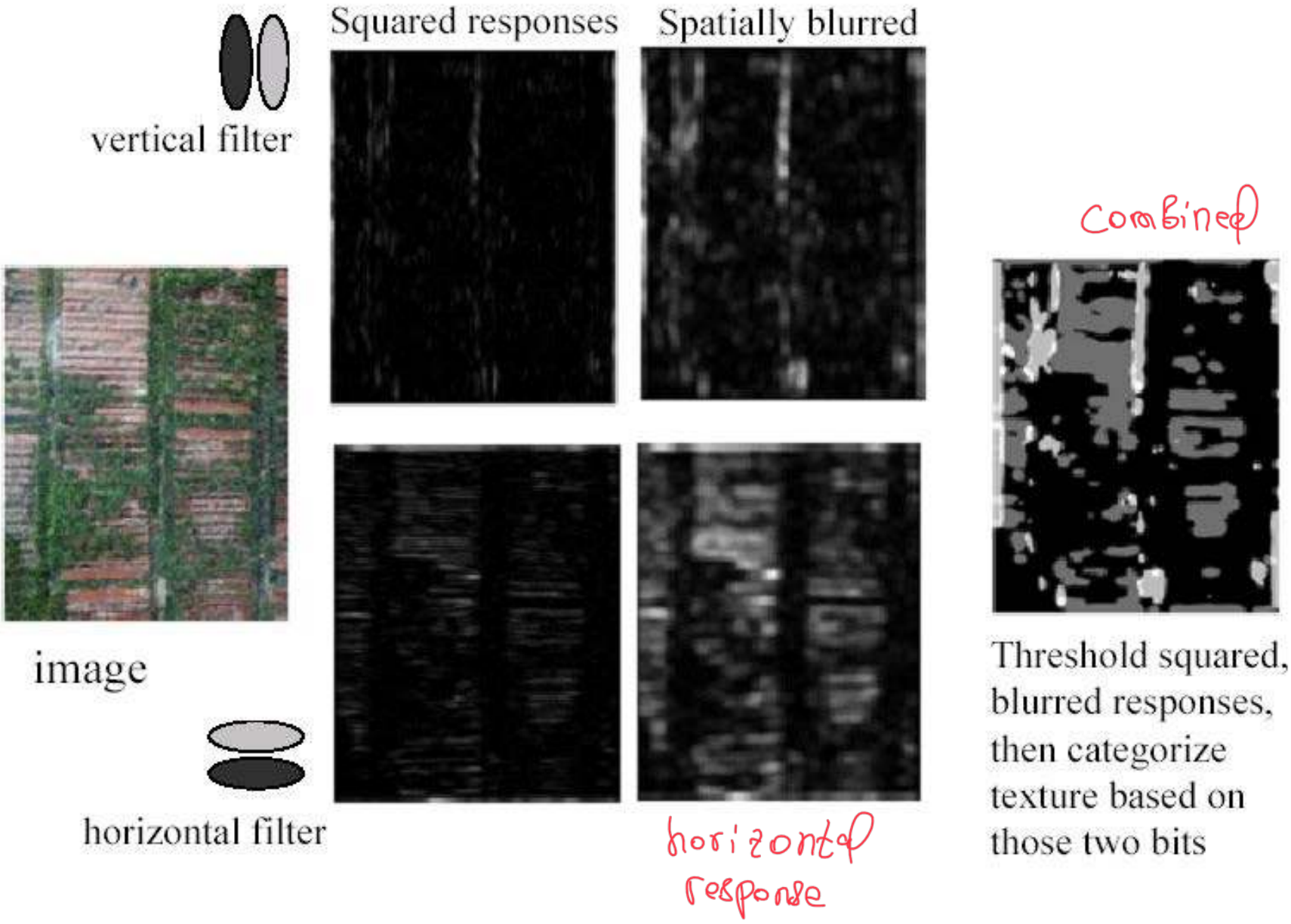


Gaussian Derivative

x and y derivatives at different scales

These filters respond to horizontal and vertical edges.

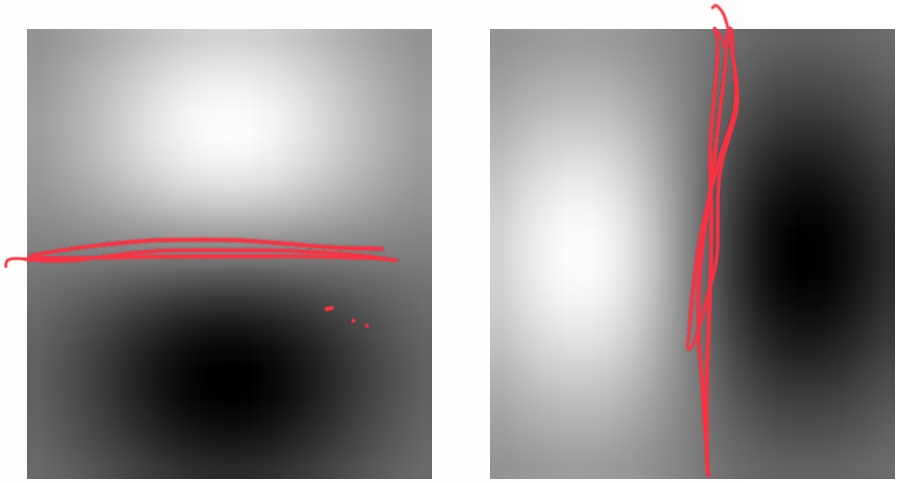
Horizontal and Vertical Structures



Oriented Filters

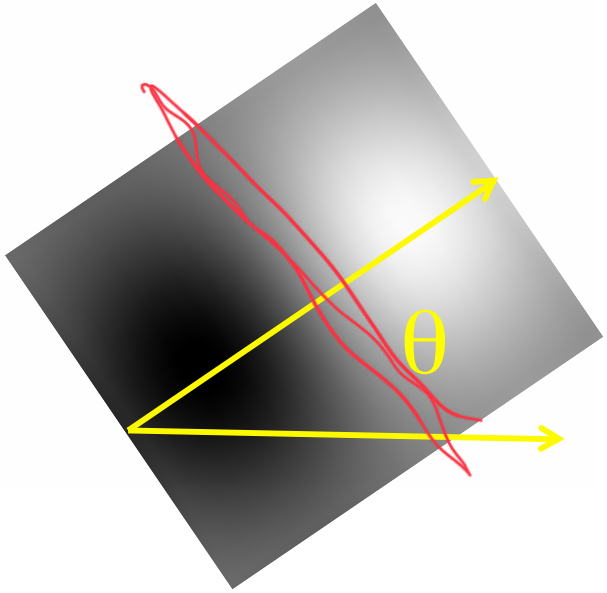
Rotated Gaussian filter

Gaussian function → weighted avg where central pixels have the most influence and the influence decreases for pixels further away

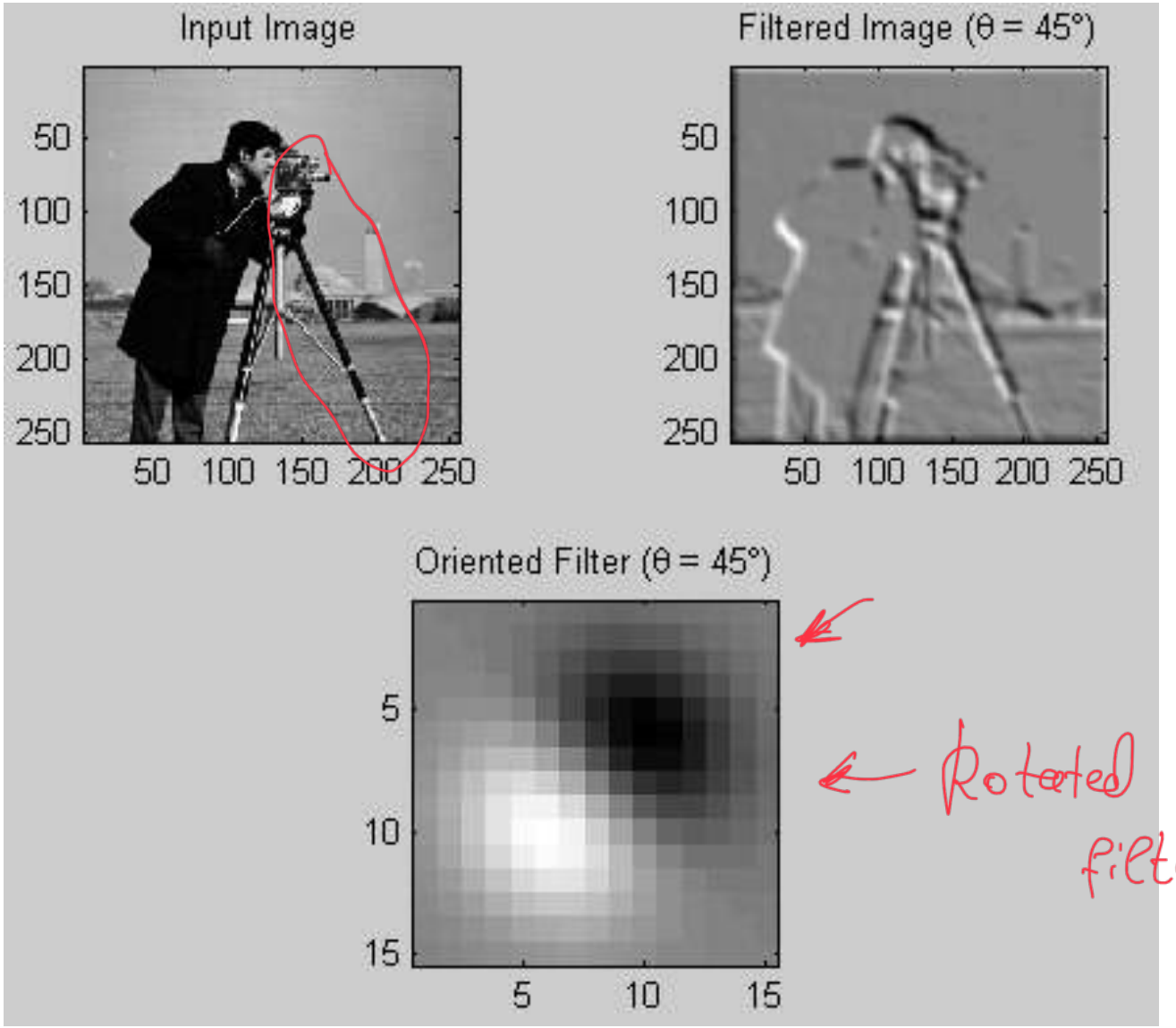


$$\frac{\partial I}{\partial \theta} = cos(\theta)\frac{\partial I}{\partial x} + sin(\theta)\frac{\partial I}{\partial y}$$

computed with Gaussian

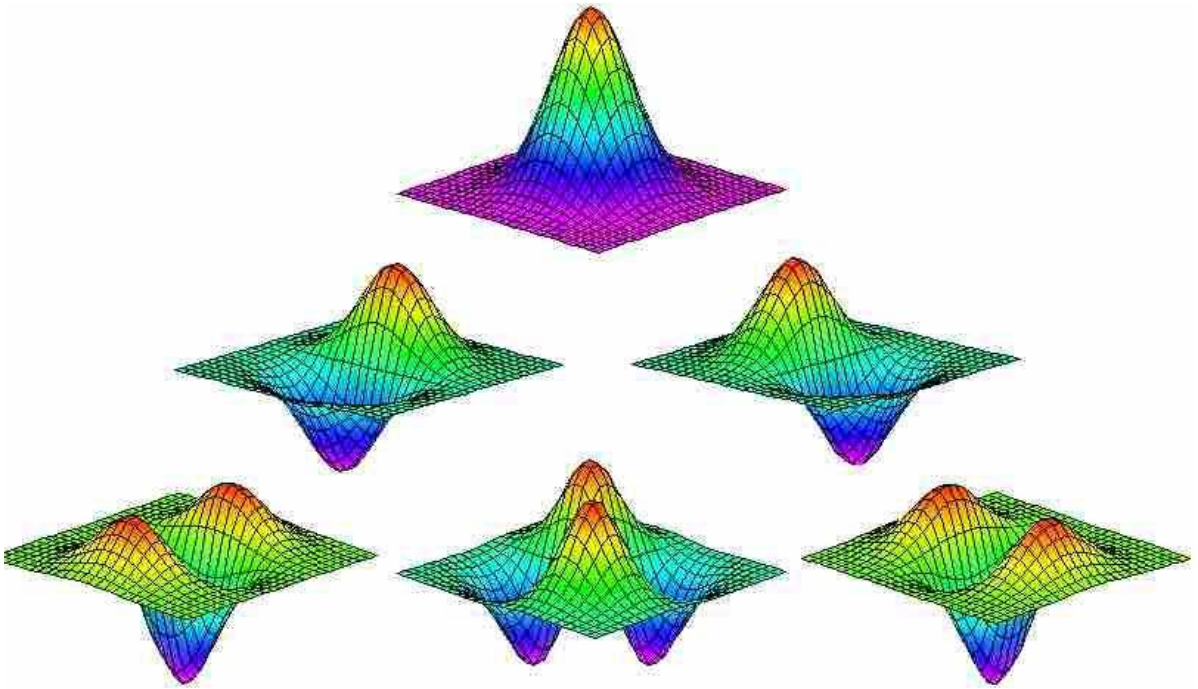


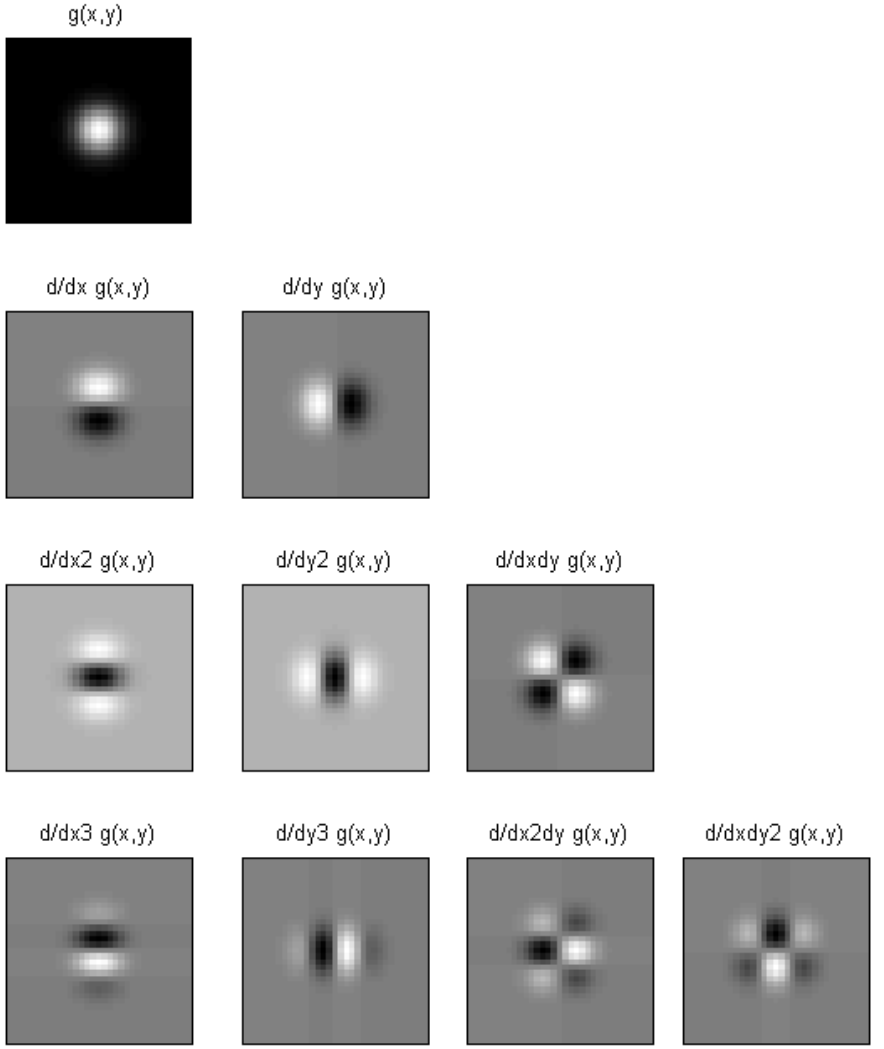
Directional Gradients



Oriented filters respond to edges in a specific direction.

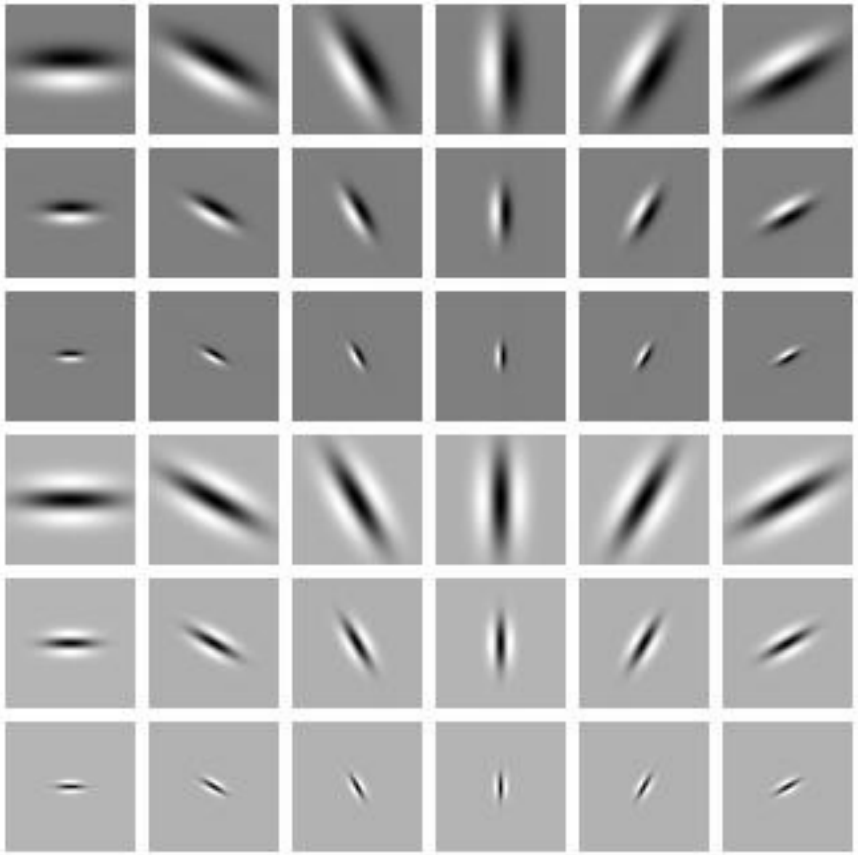
Higher Order Derivatives





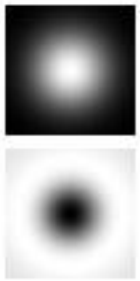
Higher-order derivatives of the Gaussian filters can be used to compute higher-order image derivatives.

Filter Bank



various rotated versions of your filters to detect structures at various orientations

- Different scales.
- Different orientations.
- Derivatives order 0, 1, 2 ..
  - ↳ detect changes in intensity at different scales



a spot filters

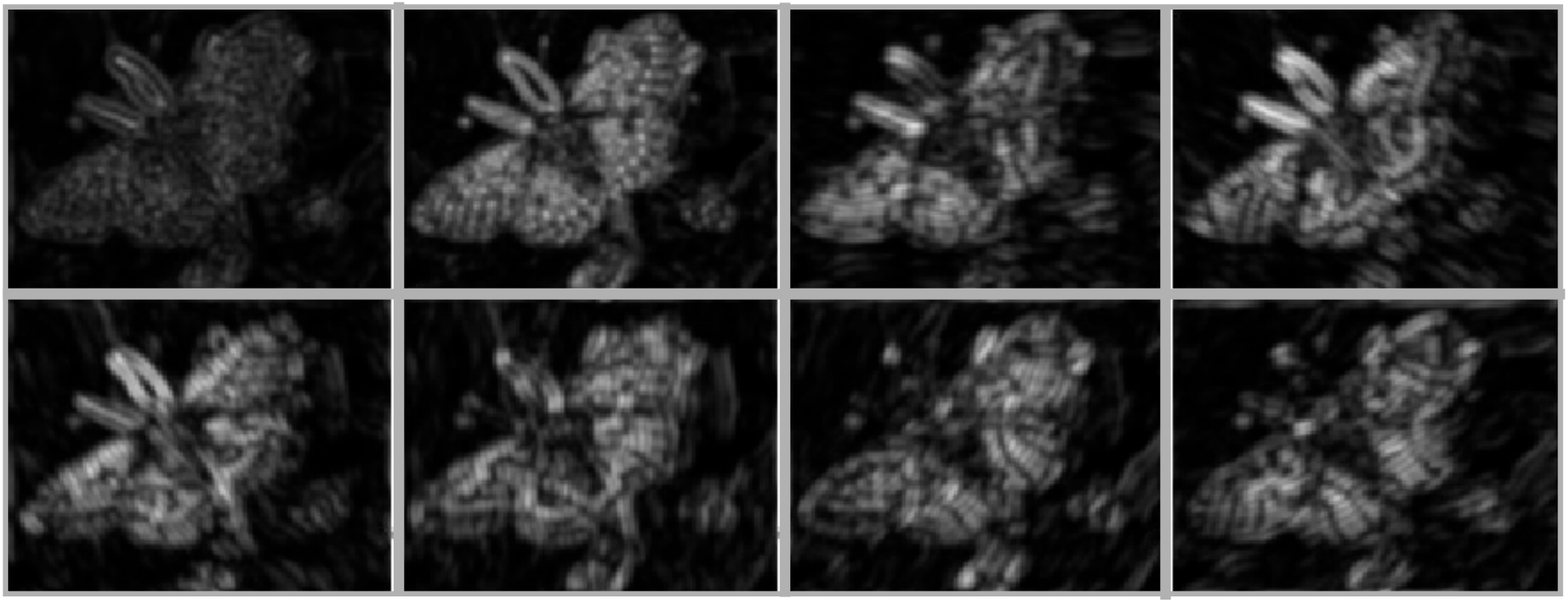
convolve with each of these filters

—> For every image pixel, compute a vector of responses to each filter.

↳ and then replace that pixel with the latter computed vector of responses

Filter Responses: Small Scales

Local Smoothing



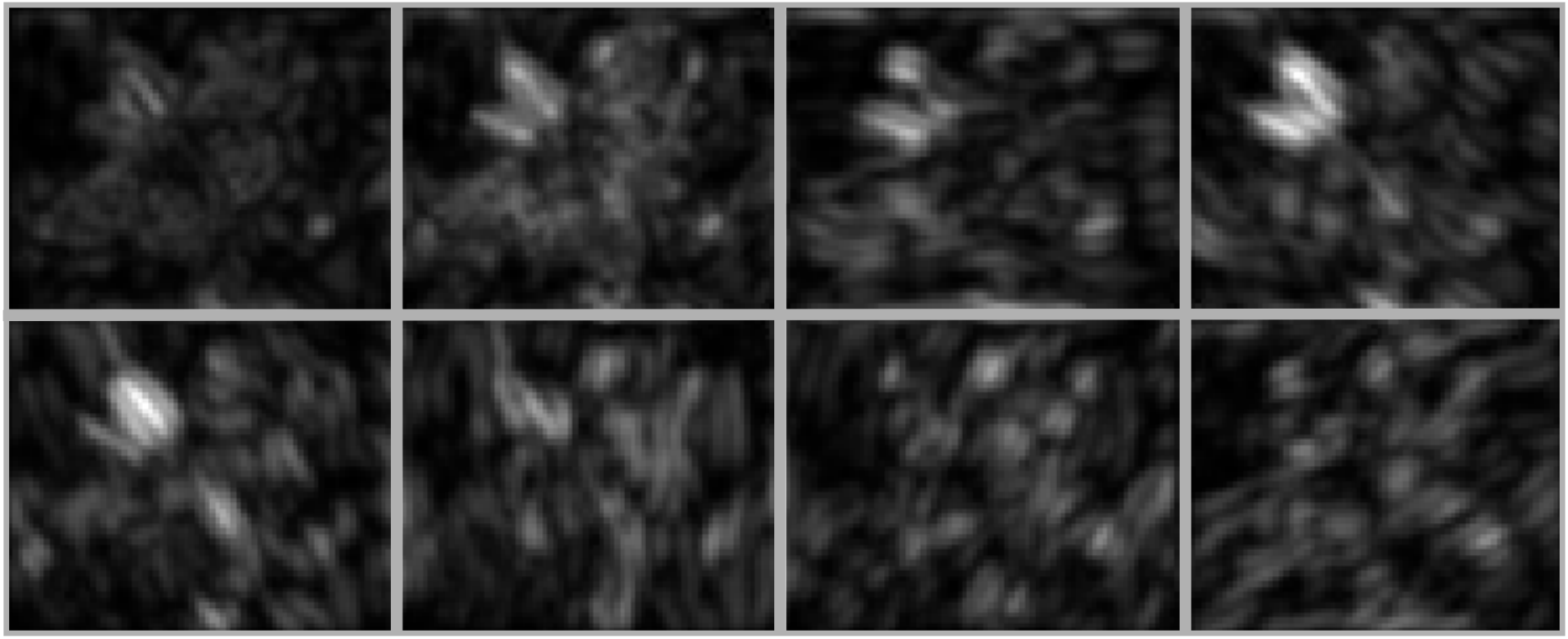
Gaussian filters with a small σ. Capture local details.

Filter Responses: Large Scales

Captures more global details in the image: global smoothing or blurring

8 responses from small scale
8 responses from large scale

pixel → 16-dimension → classifier → to classify different parts of the butterfly



Gaussian filters with a large s. Capture larger details.

Gabor Filters

smoothing and blurring operator

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:

gives sensitivity to periodic structure (like edges)

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

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

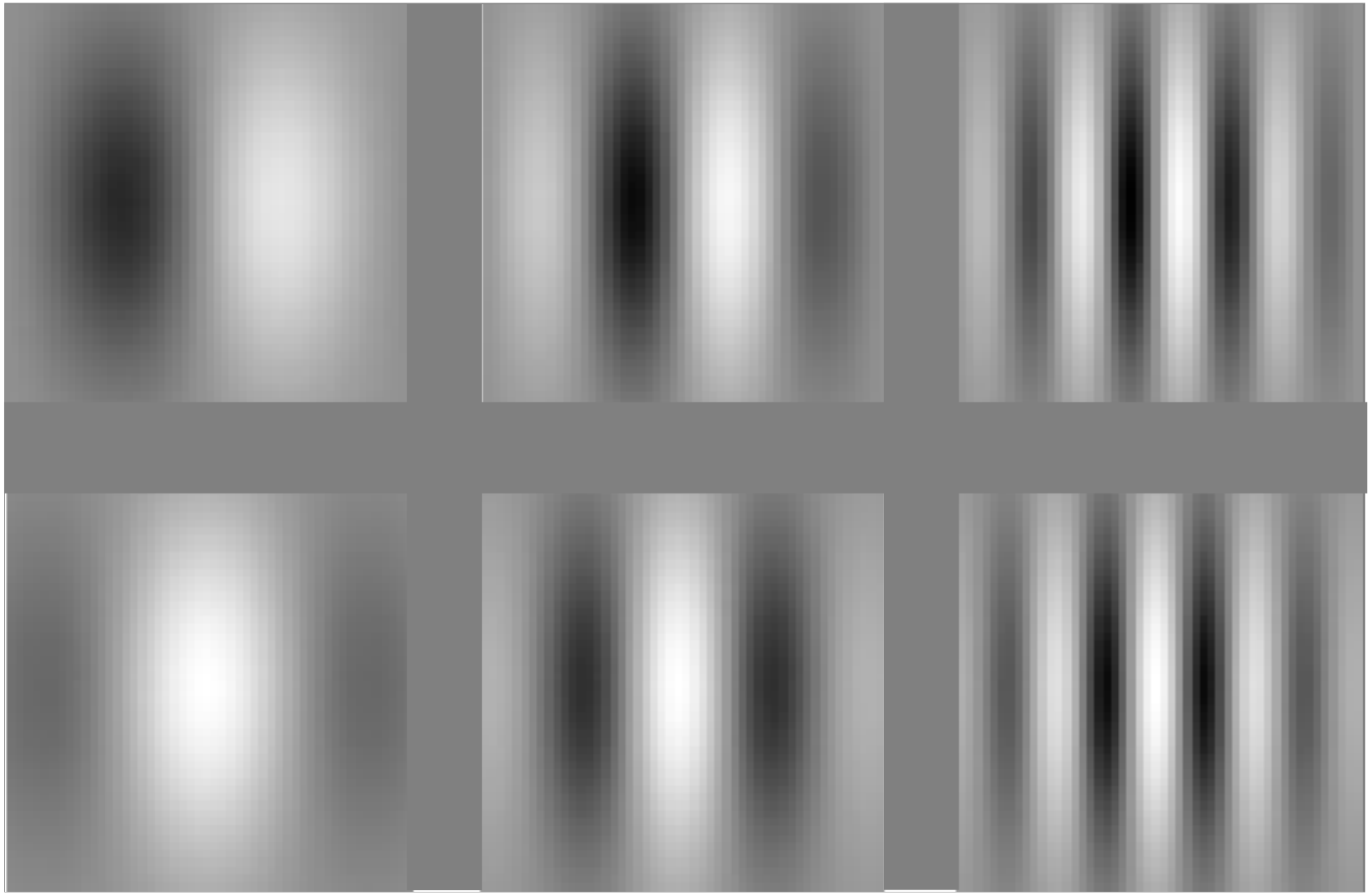
more respond strongly to the specific frequency in the img

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 of Gaussian filters

Vertical Derivatives

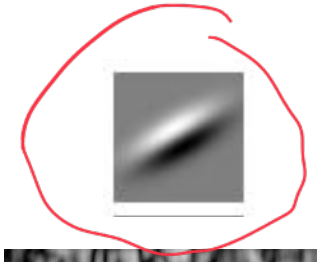
at different frequencies

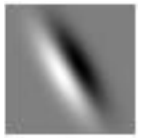


Gabor Responses

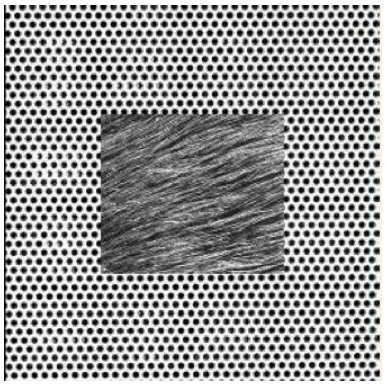
not that strongly

Filters:

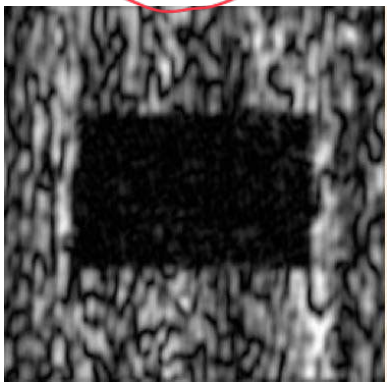


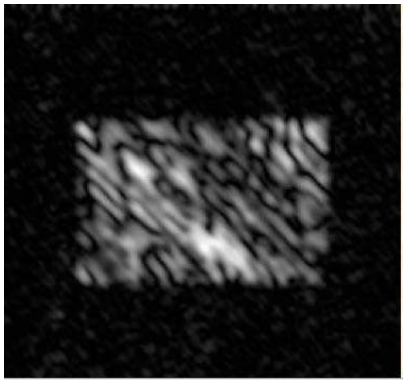


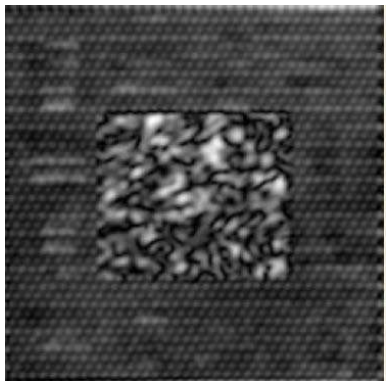
Images:

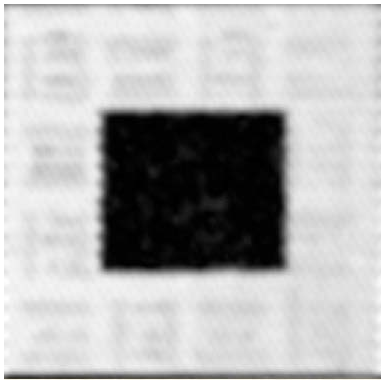


Responses:

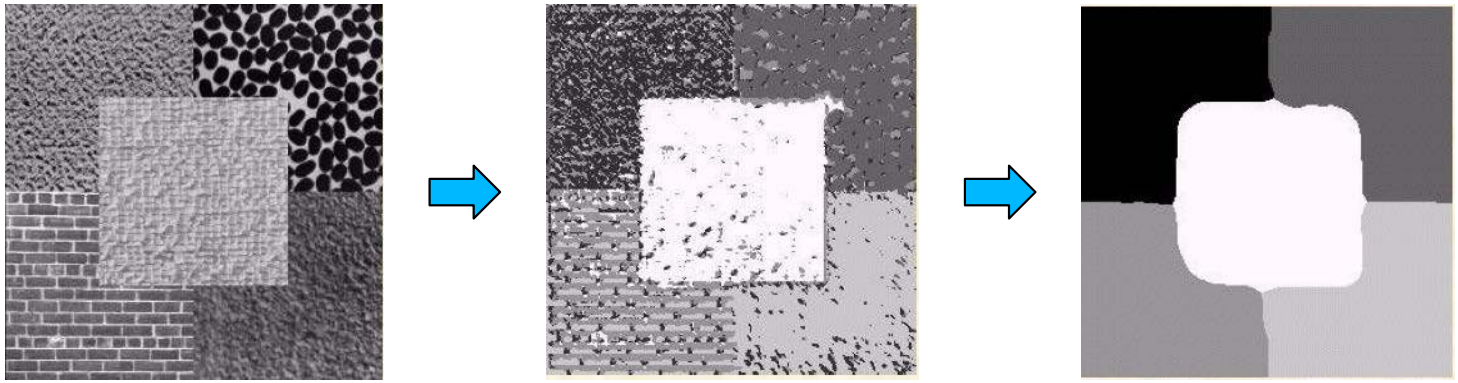








GABOR FILTER CHARACTERISTICS



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

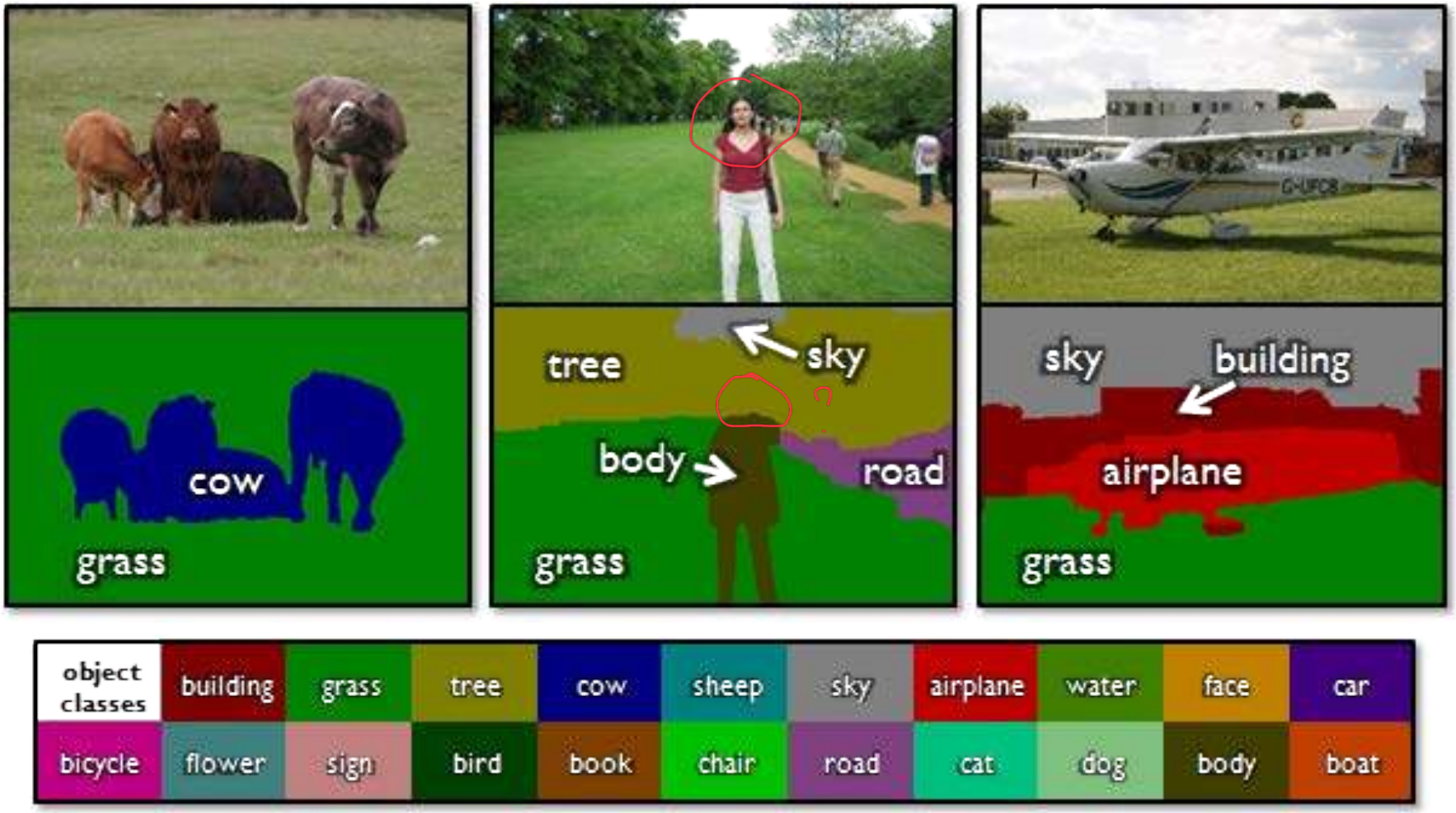
(measure of how often pixel vals change over space pix→pix)

→ rate of change of pixel intensity in an img

- 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.

ML to the Rescue: Texton Boost

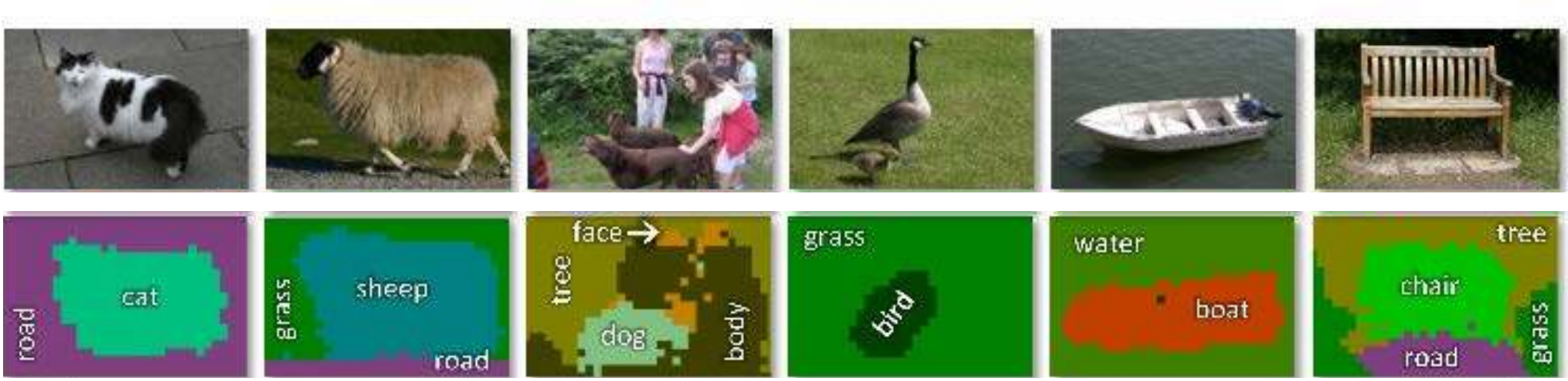


Use AdaBoost to perform classification on the output of Gabor filters.

find out which filters are useful
and do segmentation on the basis
they have ~ texture

Shotton et al., ECCV'06

ML to the Rescue: Texton Forests

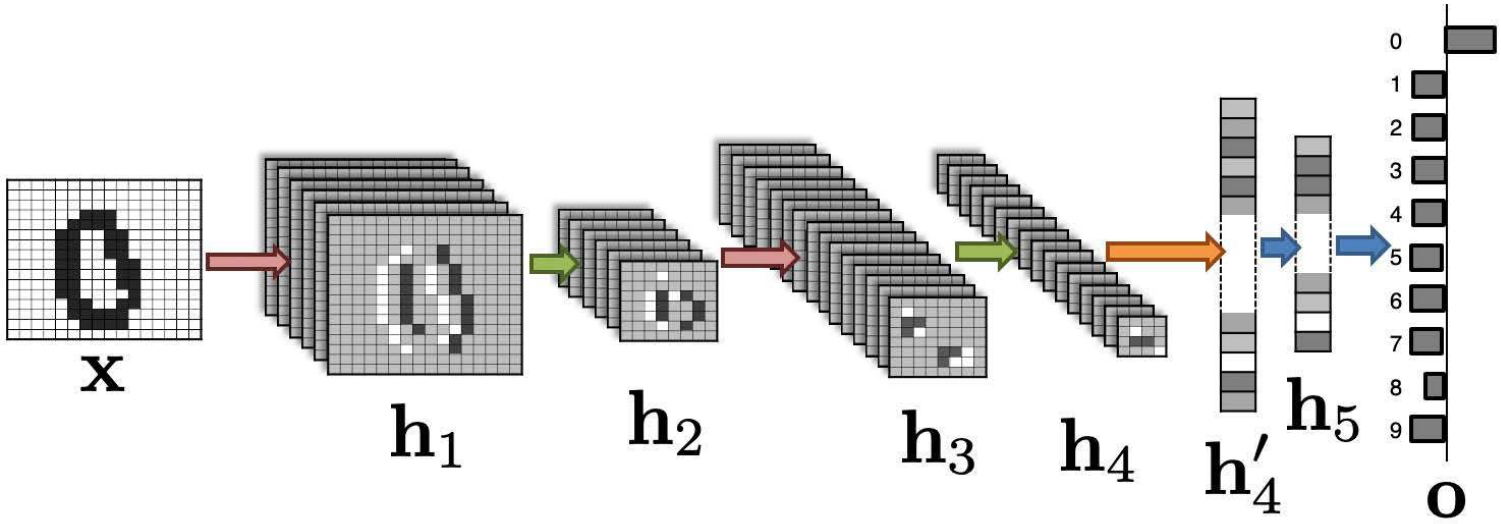


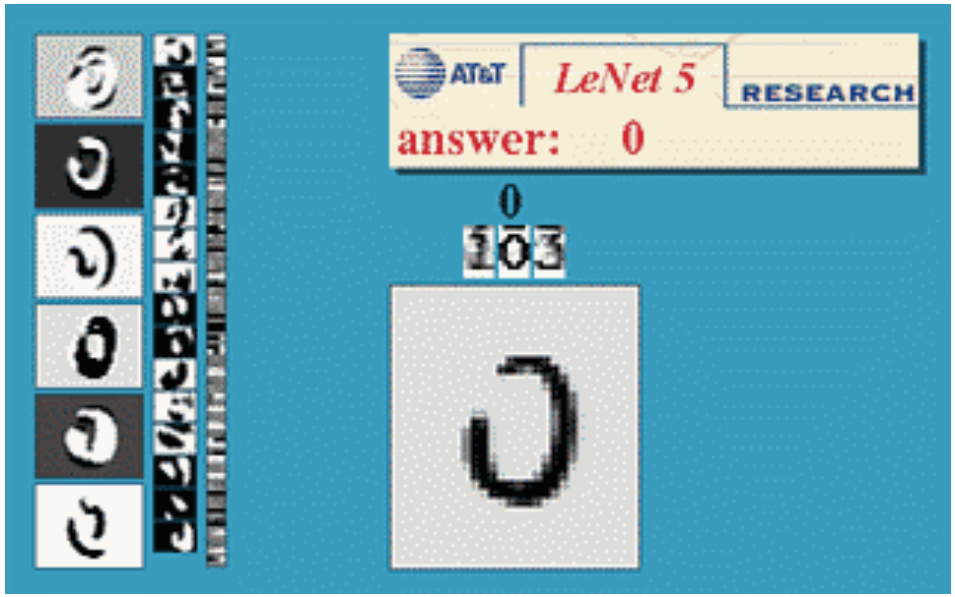
Ensemble learning (assembled classifiers) methods

- Using Decision Forests to perform classification on the output of Gabor filters works better in this case.

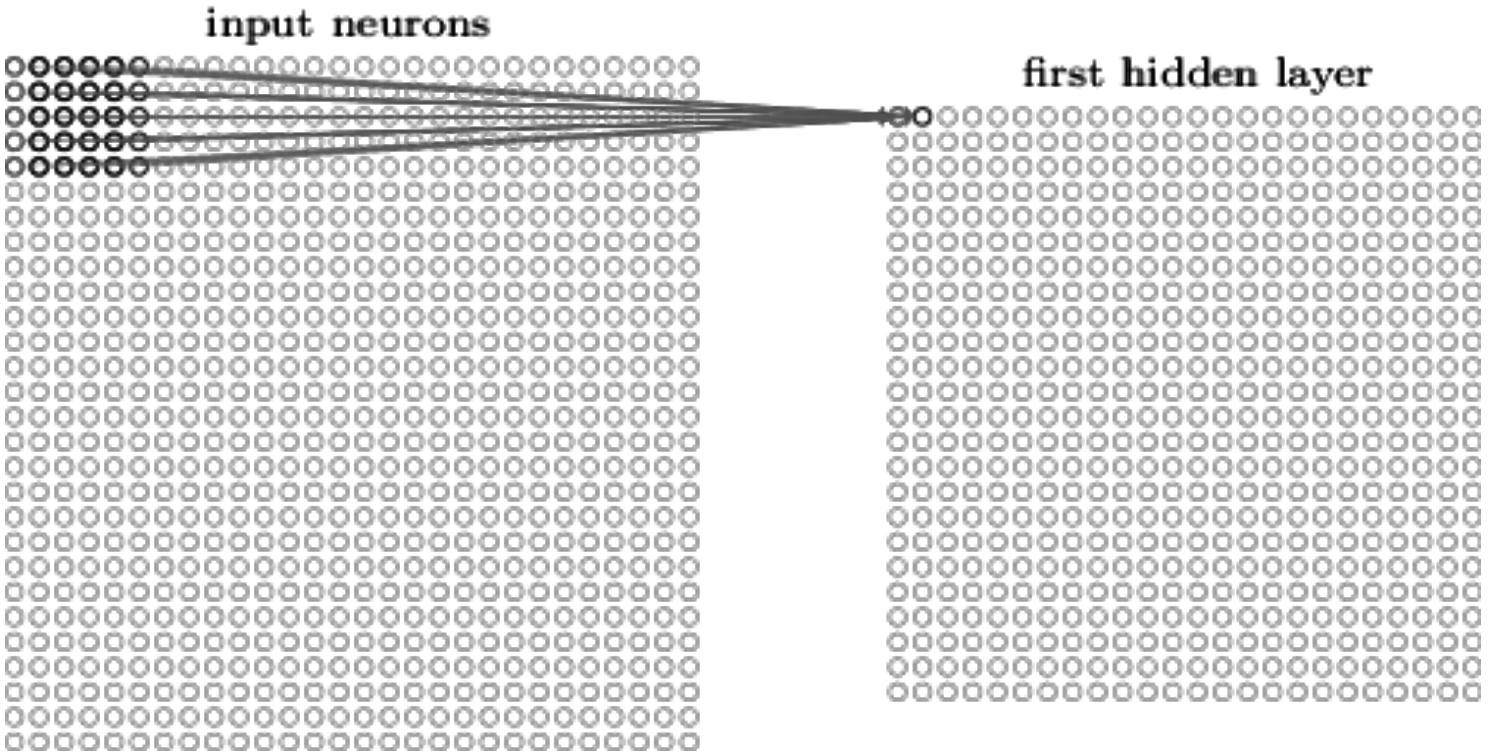
- But what works even better, is .....

Reminder: ConvNets



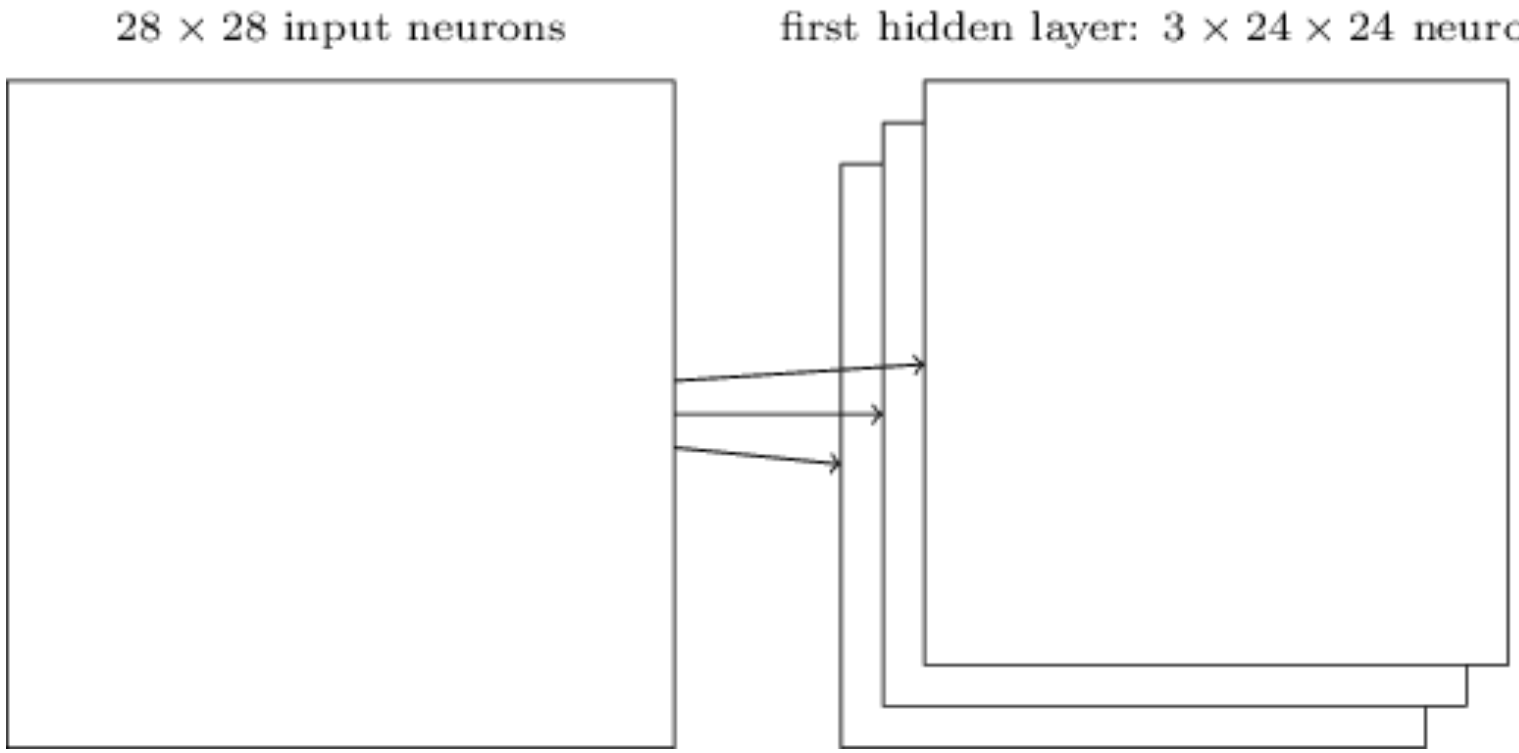


Reminder: Convolutional Layer

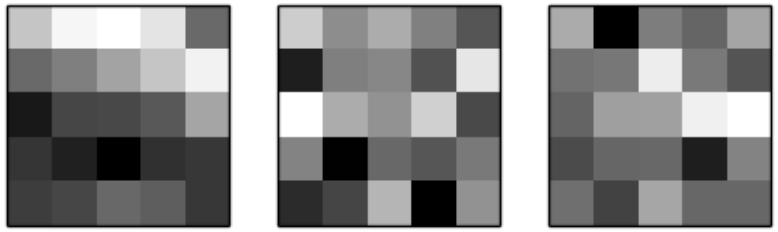


$$\sigma\left(b + \sum_{x=0}^{n_x}\sum_{y=0}^{n_y} w_{x,y} a_{i+x,j+y}\right)$$

Reminder: Feature Maps



Filters:

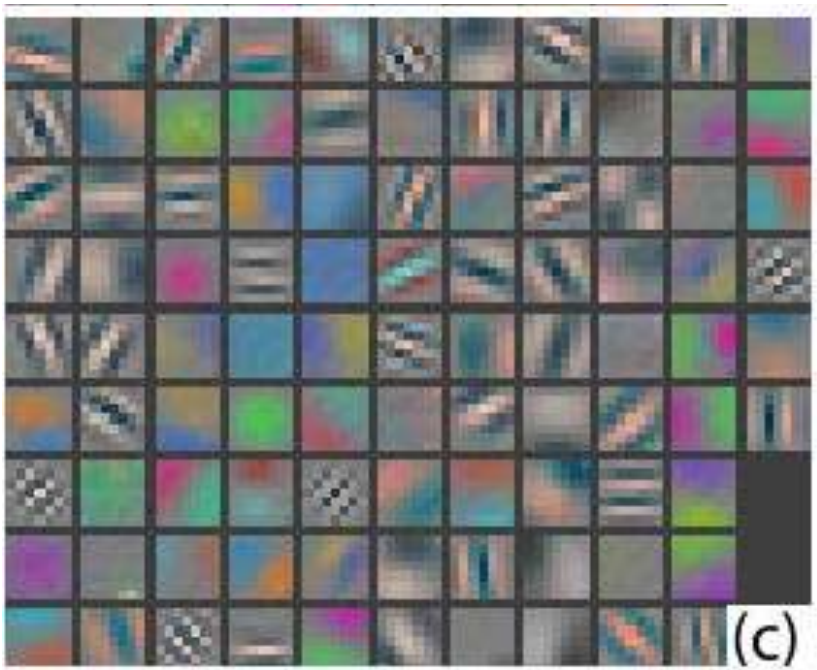


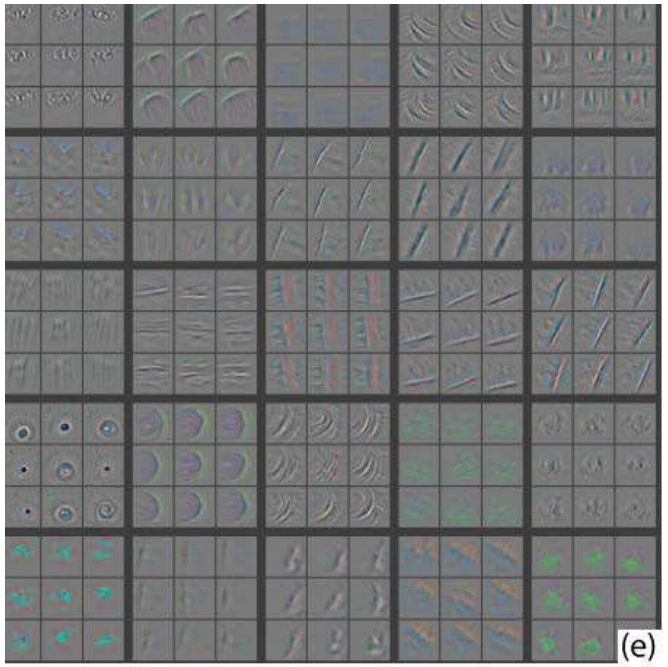
→ It learns the weights

Convolve with different filters and then train network

Learned Feature Maps

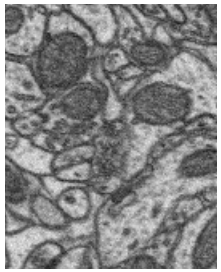
ImageNet

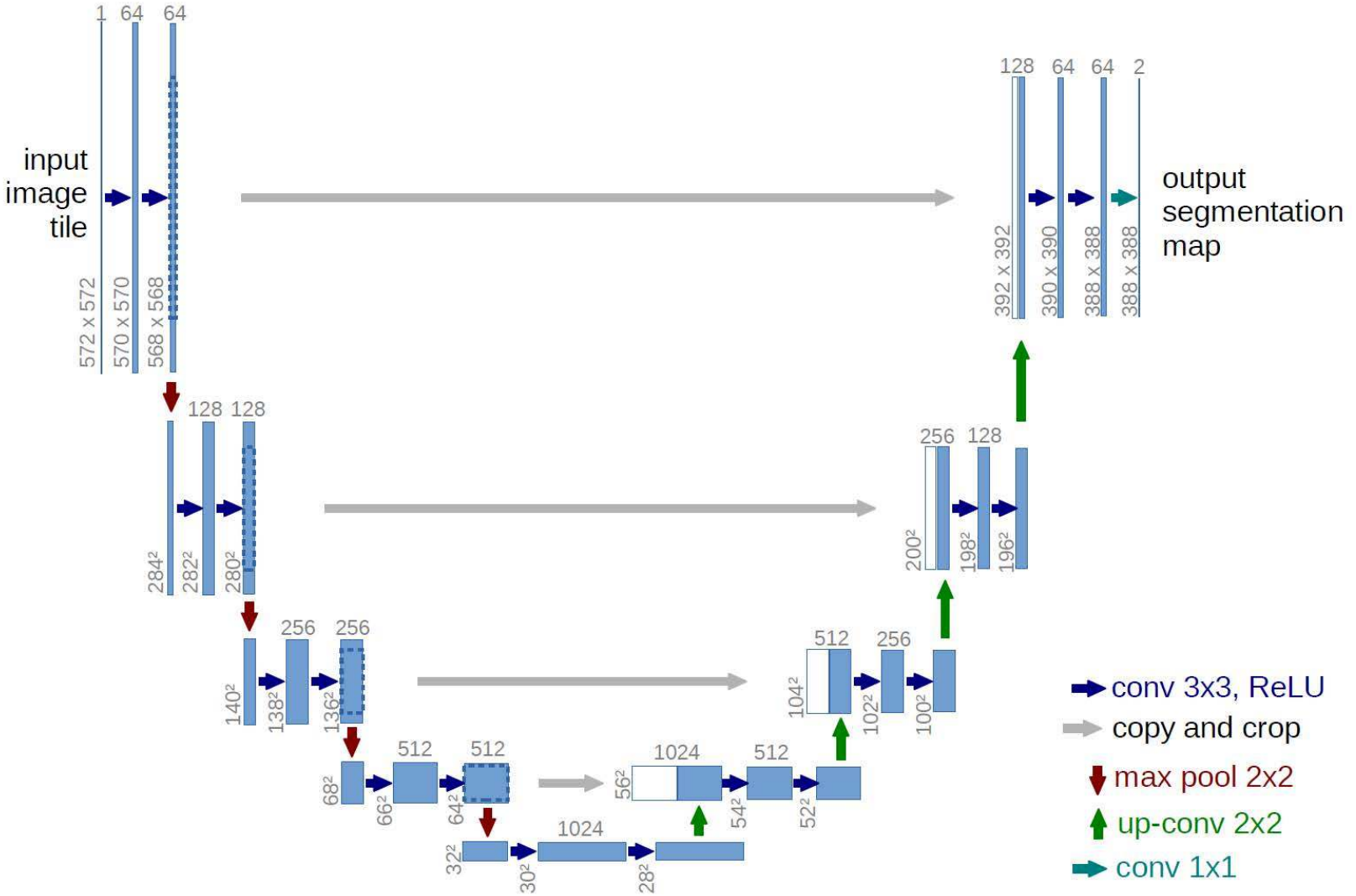




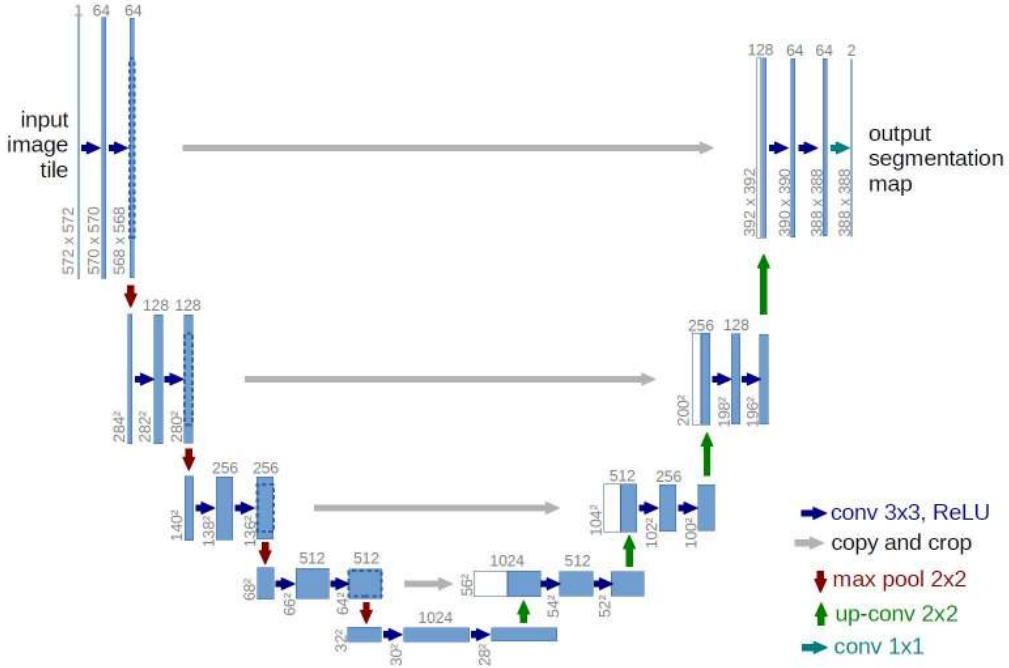
- Some of these convolutional filters look very Gabor like.
- The network requires a large training set to learn an effective filter bank. (Gabor-like filters)
- The older techniques still have their place in the absence of such training sets. manually choose Gabor filters

Reminder: U-Net Architecture

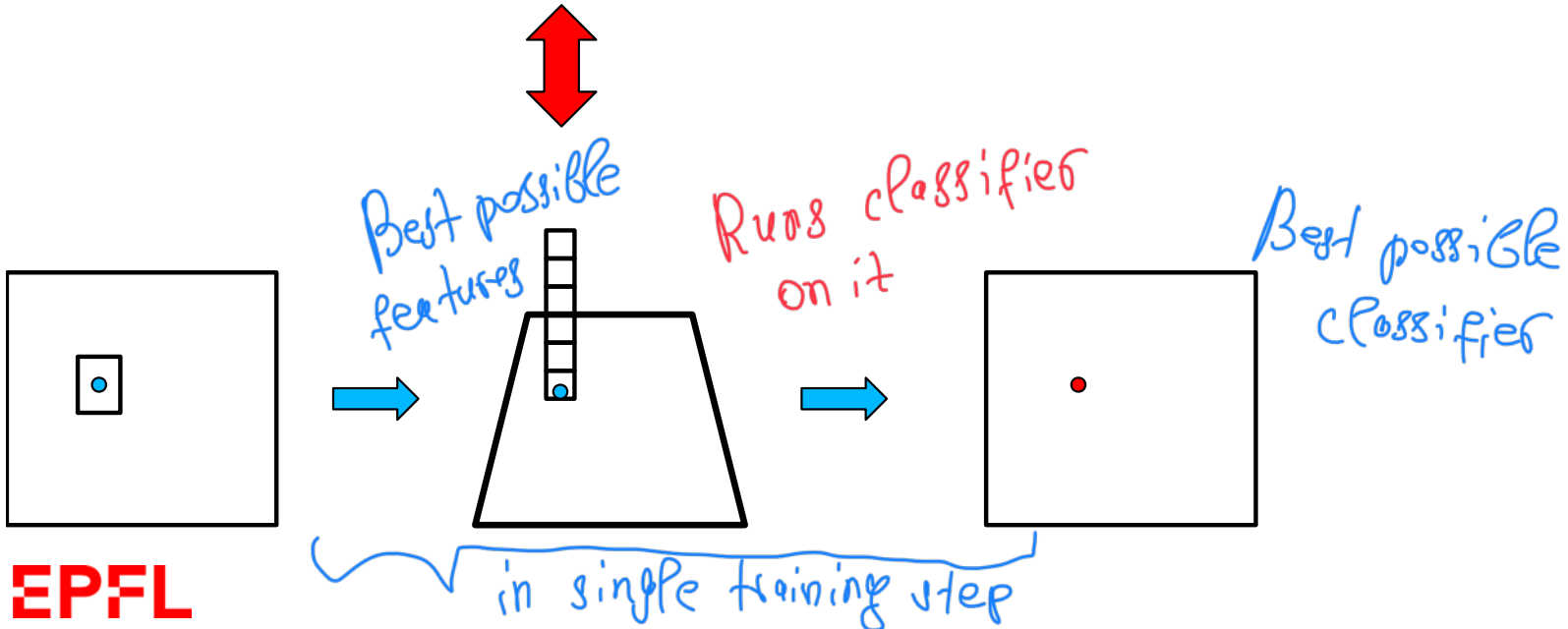




Reminder: Potential Interpretation



A key role of the ConvNet is to generate for every output pixel a feature vector containing the output of all the intermediate layers.



In Short

Texture is a key property of objects which is

- Non local → ✗ texture of the pixel
- Non trivial to measure
- Subject to deformations
  distortions

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

➡This seems to be exactly what Convolutional Neural Nets do.