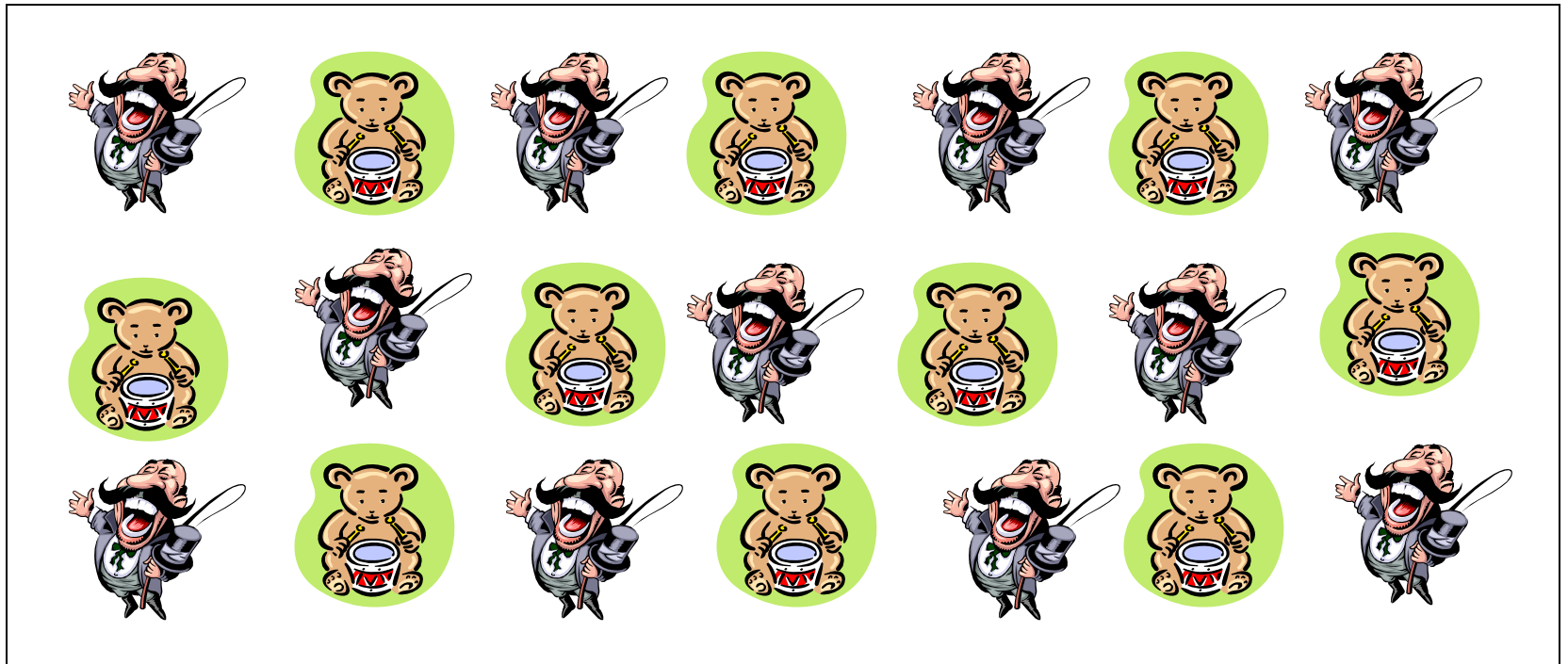


# Texture

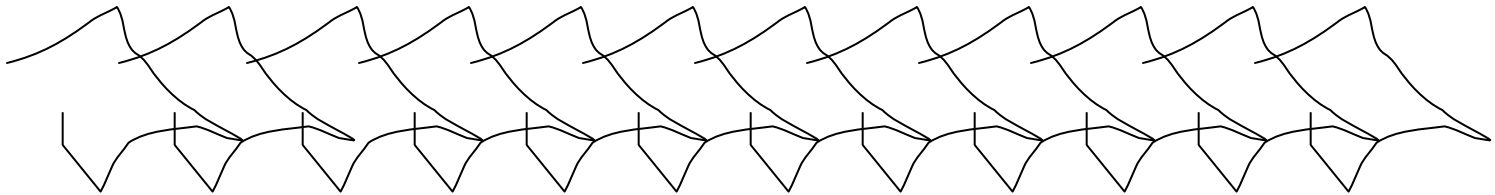
**Texture is a description of the spatial arrangement of color or intensities in an image or a selected region of an image.**

**Structural approach: a set of texels in some regular or repeated pattern**



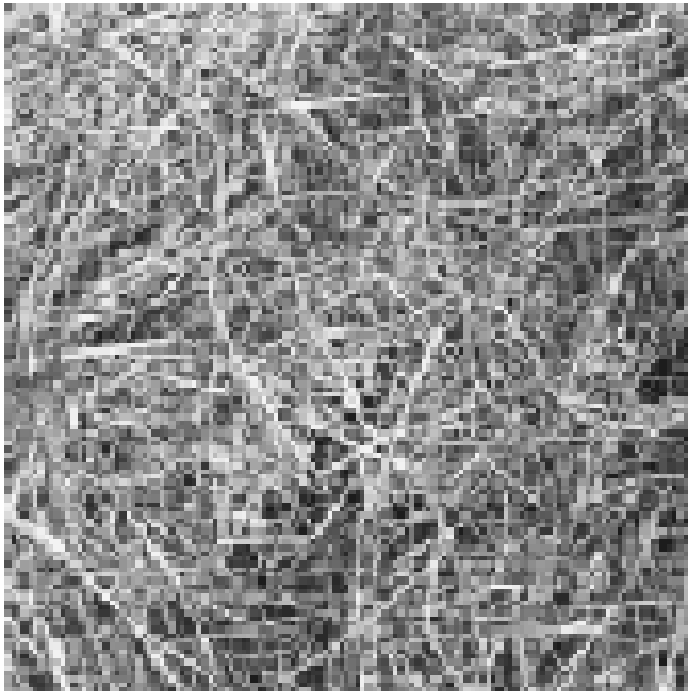
# Problem with Structural Approach

**How do you decide what is a texel?**

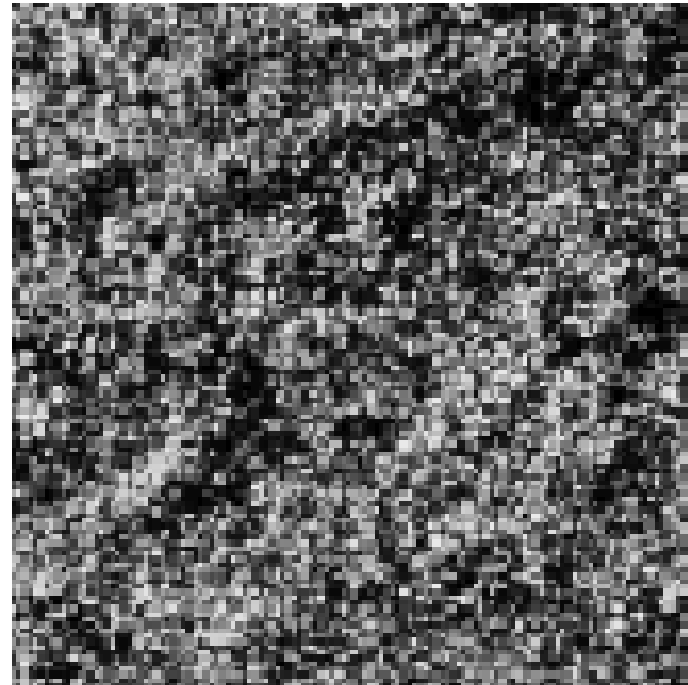


**Ideas?**

# Natural Textures from VisTex



**grass**



**leaves**

**What/Where are the texels?**

# The Case for Statistical Texture

- Segmenting out texels is difficult or impossible in real images.
- Numeric quantities or statistics that describe a texture can be computed from the gray tones (or colors) alone.
- This approach is less intuitive, but is computationally efficient.
- It can be used for both classification and segmentation.

# Some Simple Statistical Texture Measures

## 1. Edge Density and Direction

- Use an edge detector as the 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

# Two Edge-based Texture Measures

1. edgeness per unit area

$$F_{\text{edgeness}} = |\{ p \mid \text{gradient\_magnitude}(p) \geq \text{threshold} \}| / N$$

where  $N$  is the size of the unit area

2. edge magnitude and direction histograms

$$F_{\text{magdir}} = ( H_{\text{magnitude}}, H_{\text{direction}} )$$

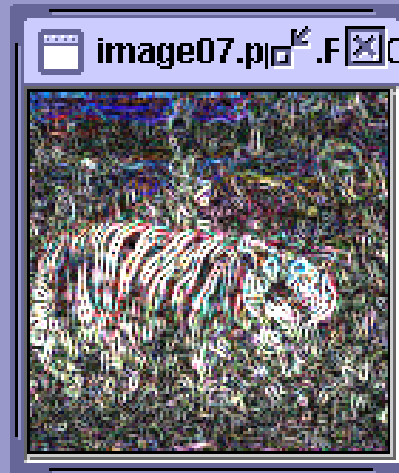
where these are the normalized histograms of gradient magnitudes and gradient directions, respectively.

# Example

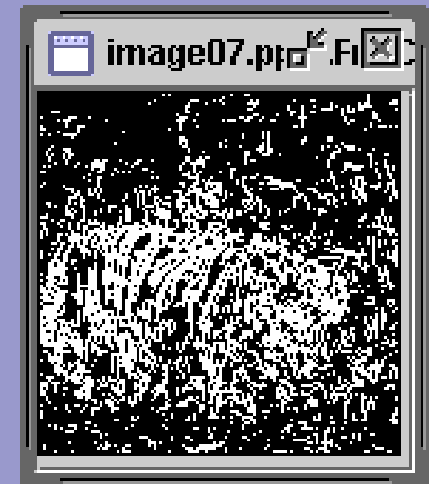
Original Image



Frei-Chen  
Edge Image

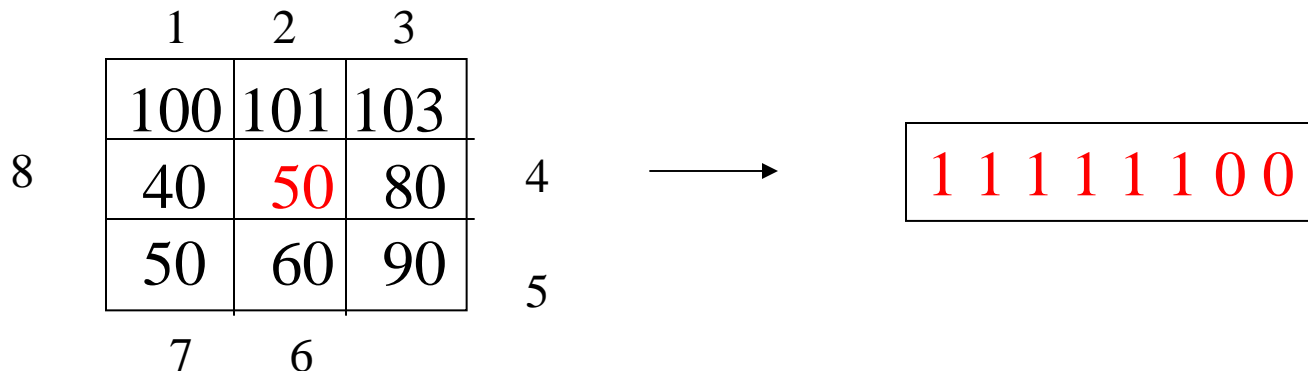


Thresholded  
Edge Image



# Local Binary Pattern Measure

- For each pixel  $p$ , create an 8-bit number  $b_1 b_2 b_3 b_4 b_5 b_6 b_7 b_8$ , where  $b_i = 0$  if neighbor  $i$  has value less than or equal to  $p$ 's value and 1 otherwise.
- Represent the texture in the image (or a region) by the histogram of these numbers.





# Example

Fids (Flexible Image Database System) is retrieving images similar to the query image using LBP texture as the texture measure and comparing their LBP histograms

## Fids demo

The screenshot displays the Fids demo interface. At the top, a grid of six images is shown, with the first image (a garden scene) highlighted by a red border. Below the grid, there are navigation buttons: "Random", "Go", "ZoomIn", and a right-pointing arrow. To the right of these buttons, it says "Found 191 matches. Displaying 1 - 6".

Below the navigation buttons, there are two columns of distance measures. The first column has checkboxes for "ColorHistL14x4x4", "ColorHist8x8x8" (which is selected and highlighted with a dashed border), "SobelEdgeHist", "LBPHist" (which is checked), "fleshiness", and "Wavelets". The second column has a slider for "loose ... strict" with a value of 5.

To the right of the distance measures, there is a radio button menu with three options: "And" (selected), "Or", and "Sum".

At the bottom of the interface, it says "Server Connected".

# Example

## Fids demo

Low-level measures don't always find semantically similar images.

The screenshot shows the Fids demo interface. At the top, a grid of six images is displayed. The first image in the top row is highlighted with a red border. Below the grid, there are navigation buttons: 'Random', 'Go', 'ZoomIn', and a right arrow. The text 'Found 119 matches. Displaying 1 - 6' is shown. Below the navigation buttons, there are controls for distance measures and logical operators. The distance measures section includes checkboxes for 'ColorHistL14x4x4', 'ColorHist8x8x8', 'SobelEdgeHist', 'LBPHist' (checked), 'fleshiness', and 'Wavelets'. Each measure has a slider and a value of 5. The logical operators section includes radio buttons for 'And' (selected), 'Or', and 'Sum'. On the right side, there are two buttons: 'Put In Cart' and 'Check Out'. Below these buttons, a text box contains the instruction 'A double click on an image means:' followed by radio buttons for 'Set query / Go' (selected) and 'Zoom in'. At the bottom left, the text 'Server Connected' is displayed.

Put In Cart

Check Out

Found 119 matches. Displaying 1 - 6

distance measures    loose ... strict

ColorHistL14x4x4    5

ColorHist8x8x8    5

SobelEdgeHist    5

LBPHist    5

fleshiness    5

Wavelets    5

And

Or

Sum

A double click on an image means:

Set query / Go

Zoom in

Server Connected

# Co-occurrence Matrix Features

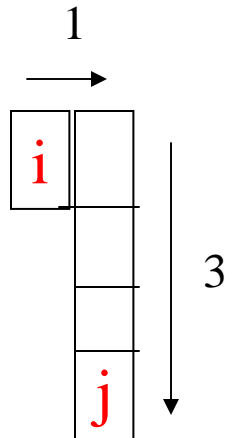
A co-occurrence matrix is a 2D array  $C$  in which

- Both the rows and columns represent a set of possible image values.
- $C_d(i,j)$  indicates how many times value  $i$  co-occurs with value  $j$  in a particular spatial relationship  $d$ .
- The spatial relationship is specified by a vector  $d = (dr,dc)$ .

# Co-occurrence Example

1	1	0	0
1	1	0	0
0	0	2	2
0	0	2	2
0	0	2	2
0	0	2	2

gray-tone  
image



$$d = (3, 1)$$

	0	1	2
0	1	0	3
1	2	0	2
2	0	0	1

co-occurrence  
matrix

$C_d$

From  $C_d$  we can compute  $N_d$ , the normalized co-occurrence matrix, where each value is divided by the sum of all the values.

# Co-occurrence Features

What do these measure?

$$\text{Energy} = \sum_i \sum_j N_d^2(i, j) \quad (7.7)$$

$$\text{Entropy} = - \sum_i \sum_j N_d(i, j) \log_2 N_d(i, j) \quad (7.8)$$

$$\text{Contrast} = \sum_i \sum_j (i - j)^2 N_d(i, j) \quad (7.9)$$

$$\text{Homogeneity} = \sum_i \sum_j \frac{N_d(i, j)}{1 + |i - j|} \quad (7.10)$$

$$\text{Correlation} = \frac{\sum_i \sum_j (i - \mu_i)(j - \mu_j) N_d(i, j)}{\sigma_i \sigma_j} \quad (7.11)$$

where  $\mu_i, \mu_j$  are the means and  $\sigma_i, \sigma_j$  are the standard deviations of the row and column sums.

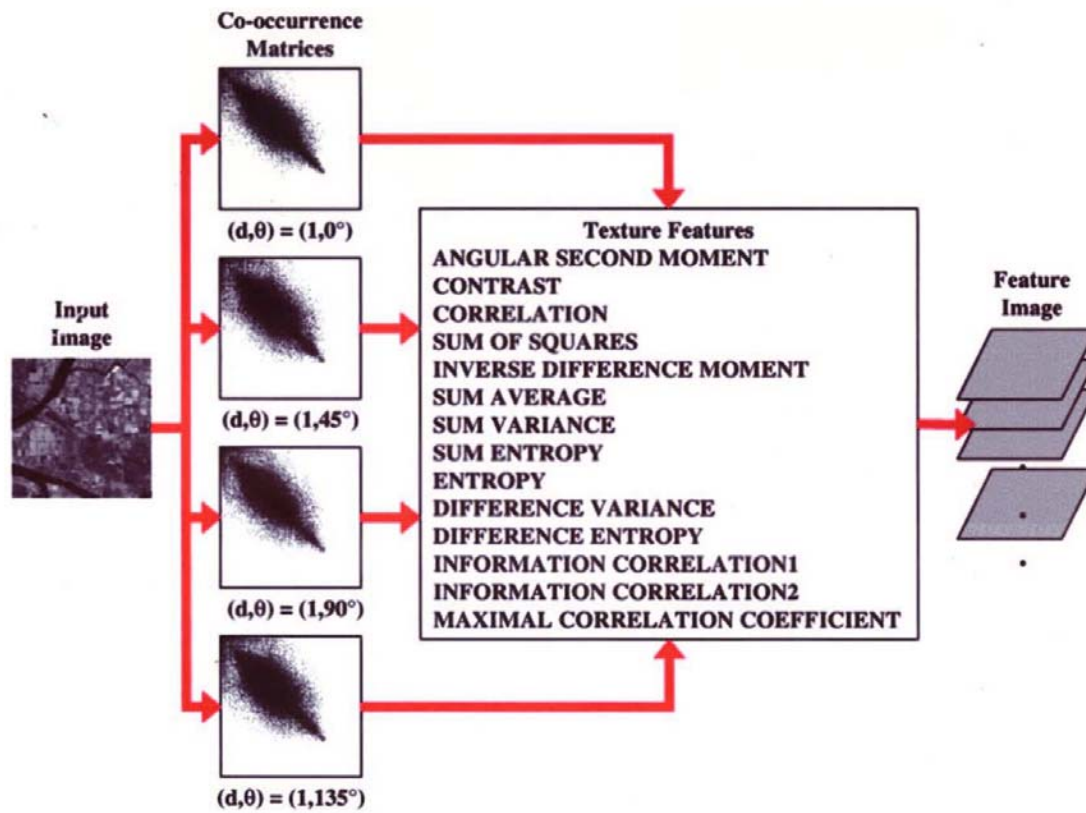
Energy measures uniformity of the normalized matrix.

# But how do you choose d?

- This is actually a critical question with **all** the statistical texture methods.
- Are the “texels” tiny, medium, large, all three ...?
- Not really a solved problem.

Zucker and Terzopoulos suggested using a  $\chi^2$  statistical test to select the value(s) of d that have the most structure for a given class of images.

# Example



# Laws' Texture Energy Features

- Signal-processing-based algorithms use texture filters applied to the image to create filtered images from which texture features are computed.
- The Laws Algorithm
  - **Filter** the input image using texture filters.
  - **Compute texture energy** by summing the absolute value of filtering results in local neighborhoods around each pixel.
  - **Combine features** to achieve rotational invariance.



# Law's texture masks (1)

$$\begin{array}{lll} \text{L5} & \text{(Level)} & = \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \end{bmatrix} \\ \text{E5} & \text{(Edge)} & = \begin{bmatrix} -1 & -2 & 0 & 2 & 1 \end{bmatrix} \\ \text{S5} & \text{(Spot)} & = \begin{bmatrix} -1 & 0 & 2 & 0 & -1 \end{bmatrix} \\ \text{R5} & \text{(Ripple)} & = \begin{bmatrix} 1 & -4 & 6 & -4 & 1 \end{bmatrix} \end{array}$$

- (L5) (Gaussian) gives a center-weighted local average
- (E5) (gradient) responds to row or col step edges
- (S5) (LOG) detects spots
- (R5) (Gabor) detects ripples

# Law's texture masks (2)

## Creation of 2D Masks

- **1D Masks are “multiplied” to construct 2D masks:**  
mask E5L5 is the “product” of E5 and L5 -

$$\begin{array}{c} \mathbf{E5} \end{array} \begin{bmatrix} -1 \\ -2 \\ 0 \\ 2 \\ 1 \end{bmatrix} \times \begin{array}{c} \mathbf{L5} \end{array} \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \end{bmatrix} = \begin{array}{c} \mathbf{E5L5} \end{array} \begin{bmatrix} -1 & -4 & -6 & -4 & -1 \\ -2 & -8 & -12 & -8 & -1 \\ 0 & 0 & 0 & 0 & 0 \\ 2 & 8 & 12 & 8 & 2 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$$

# 9D feature vector for pixel

- Subtract mean neighborhood intensity from (center) pixel
- Apply 16 5x5 masks to get 16 filtered images  $F_k$ ,  $k=1$  to 16
- Produce 16 texture energy maps using 15x15 windows

$$E_k[r,c] = \sum |F_k[i,j]|$$

- 9 features defined as follows:

L5E5/E5L5

L5R5/R5L5

E5S5/S5E5

S5S5

R5R5

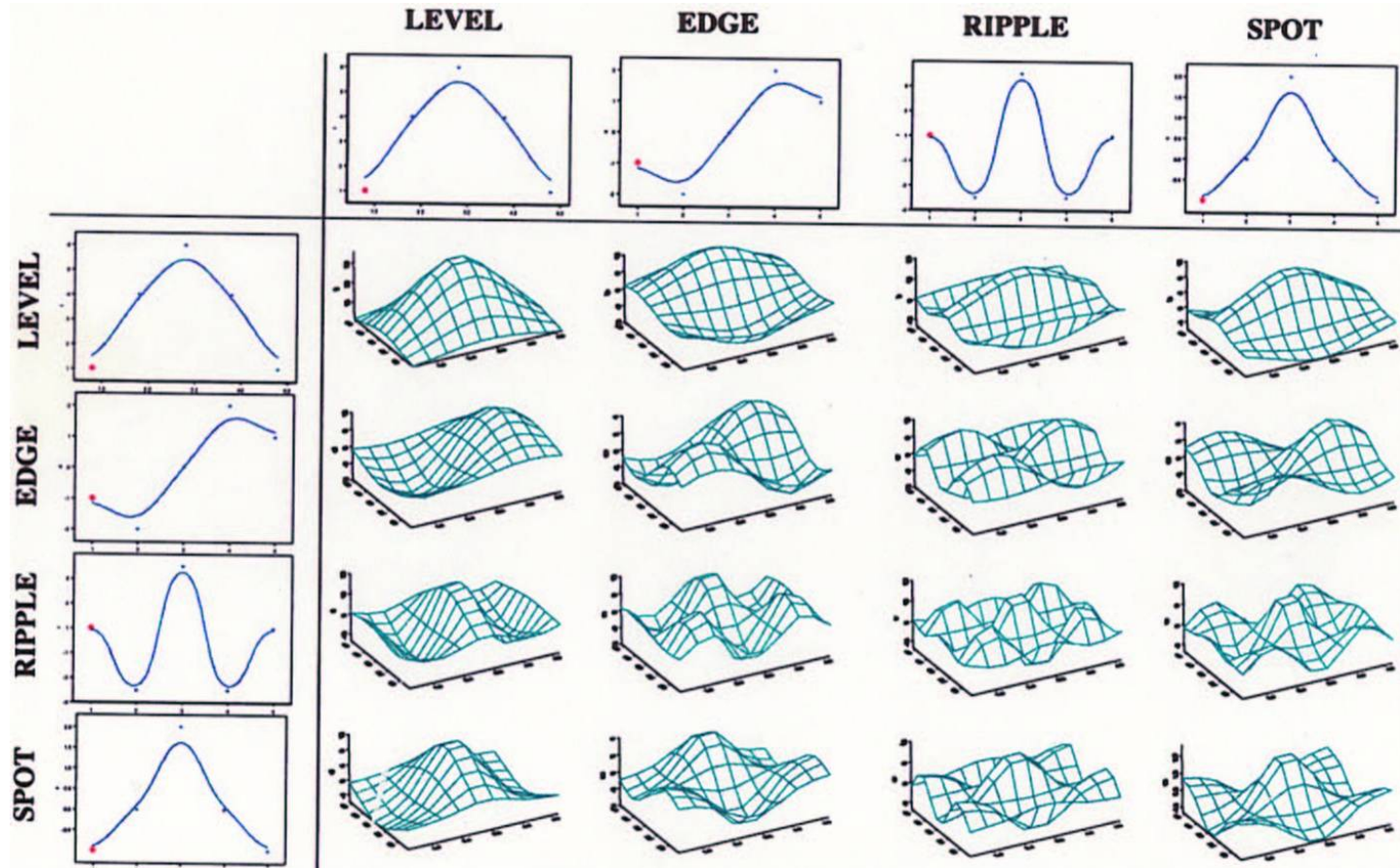
L5S5/S5L5

E5E5

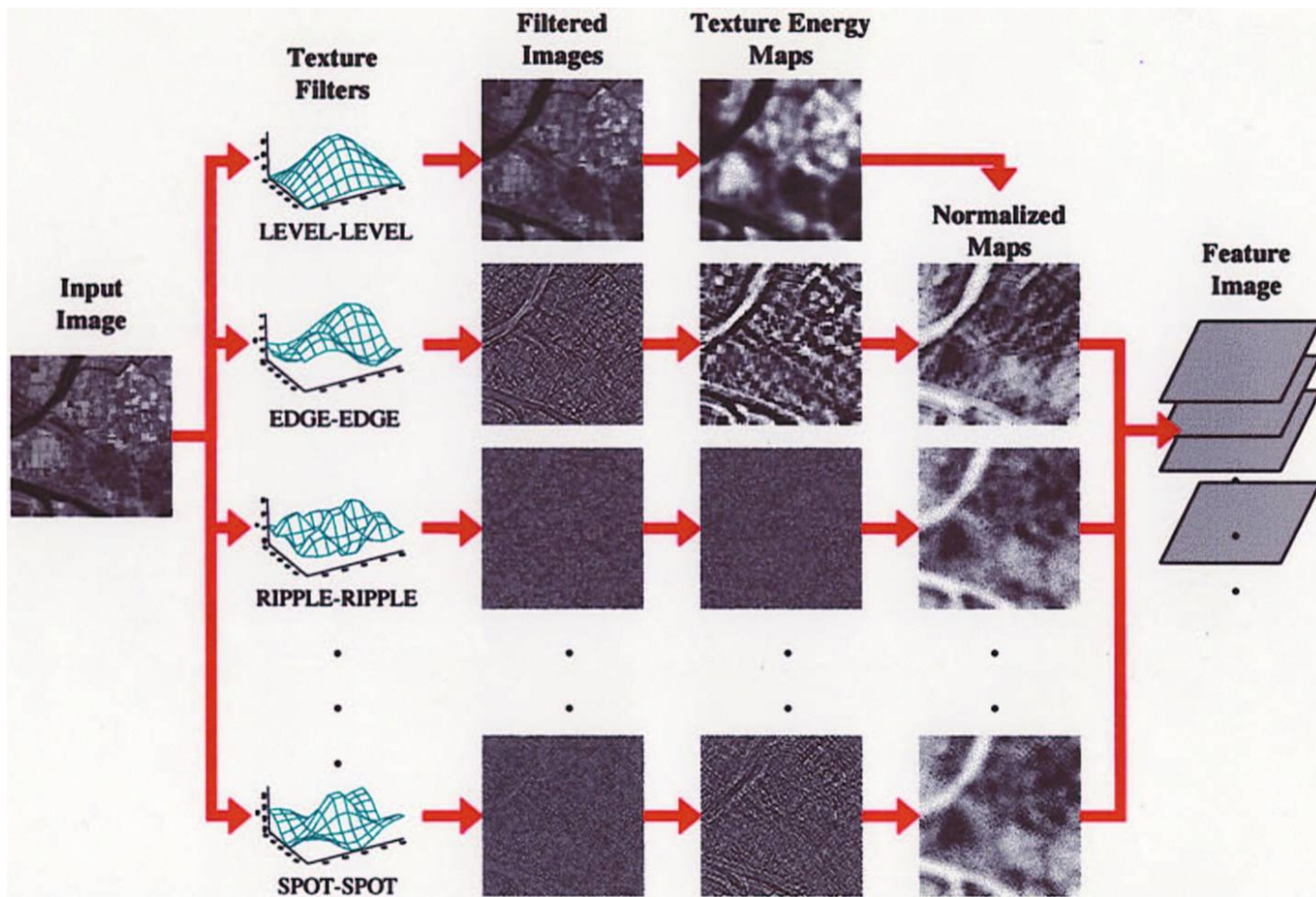
E5R5/R5E5

S5R5/R5S5

# Laws Filters



# Laws Process





# Example: Using Laws Features to Cluster

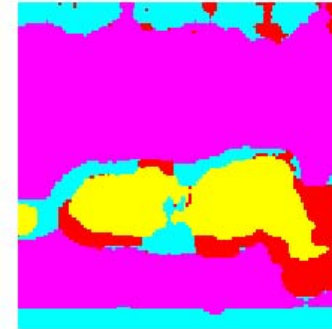
water



tiger



(a) Original image



(b) Segmentation into 4 clusters

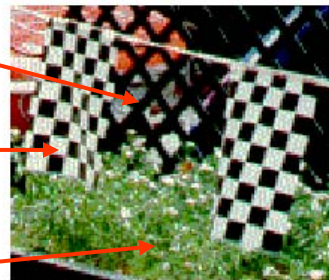
fence



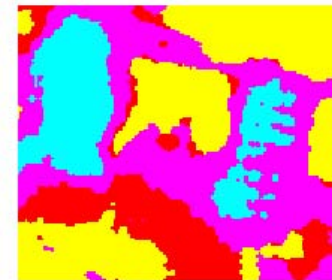
flag



grass



(c) Original image

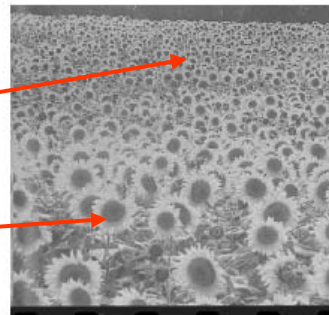


(d) Segmentation into 4 clusters

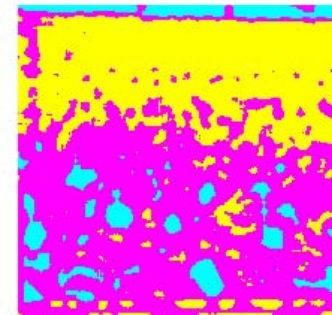
small flowers



big flowers



(e) Original image



(f) Segmentation into 3 clusters

Is there a neighborhood size problem with Laws?

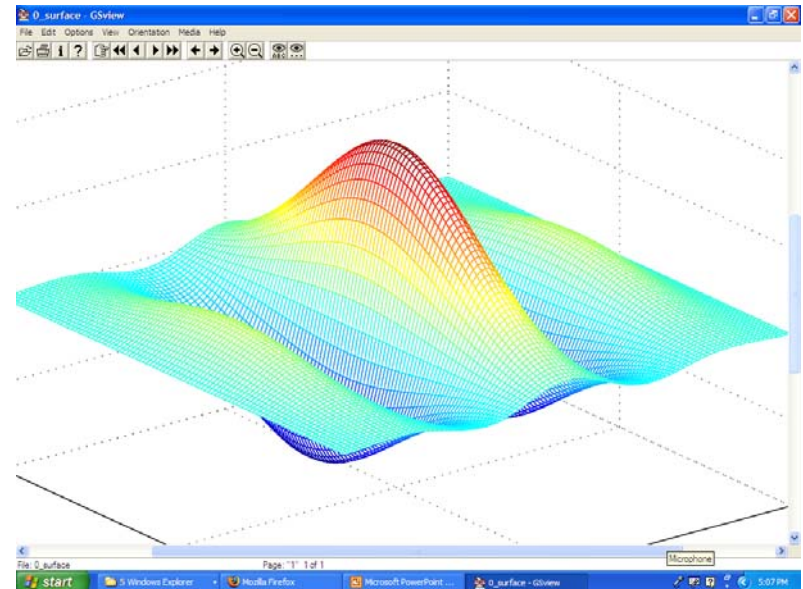
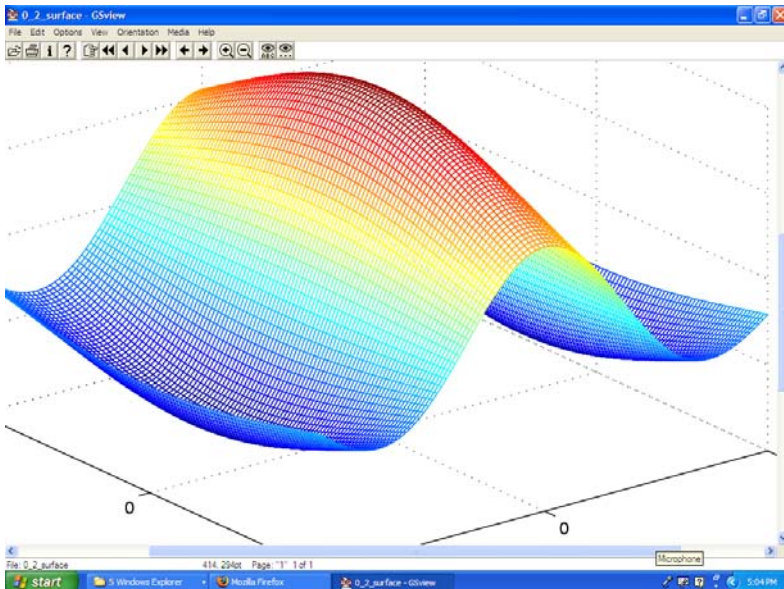
# Features from sample images

Table 7.2: Laws texture energy measures for major regions of the images of Figure 7.8.

Region	E5E5	S5S5	R5R5	E5L5	S5L5	R5L5	S5E5	R5E5	R5S5
Tiger	168.1	84.0	807.7	553.7	354.4	910.6	116.3	339.2	257.4
Water	68.5	36.9	366.8	218.7	149.3	459.4	49.6	159.1	117.3
Flags	258.1	113.0	787.7	1057.6	702.2	2056.3	182.4	611.5	350.8
Fence	189.5	80.7	624.3	701.7	377.5	803.1	120.6	297.5	215.0
Grass	206.5	103.6	1031.7	625.2	428.3	1153.6	146.0	427.5	323.6
Small flowers	114.9	48.6	289.1	402.6	241.3	484.3	73.6	158.2	109.3
Big flowers	76.7	28.8	177.1	301.5	158.4	270.0	45.6	89.7	62.9
Borders	15.3	6.4	64.4	92.3	36.3	74.5	9.3	26.1	19.5

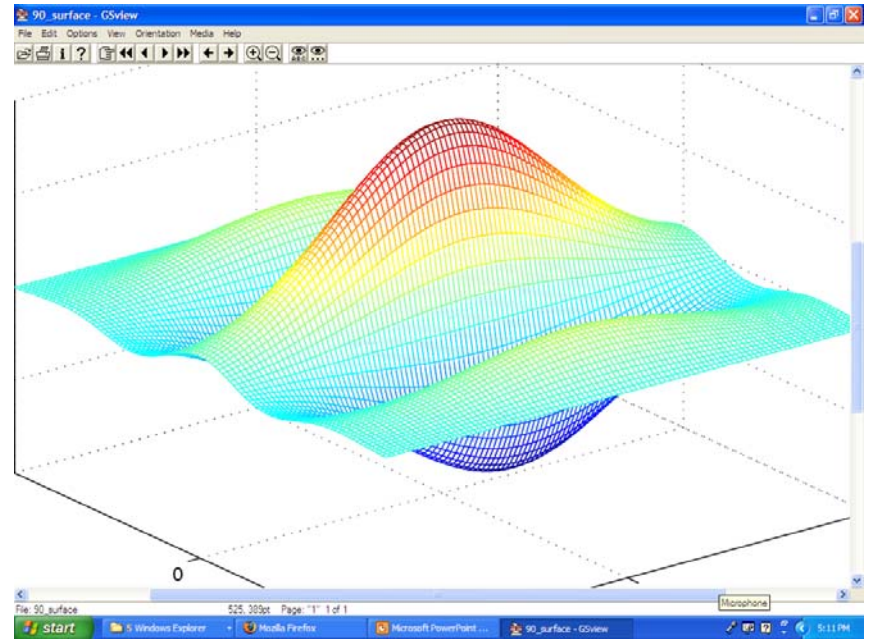
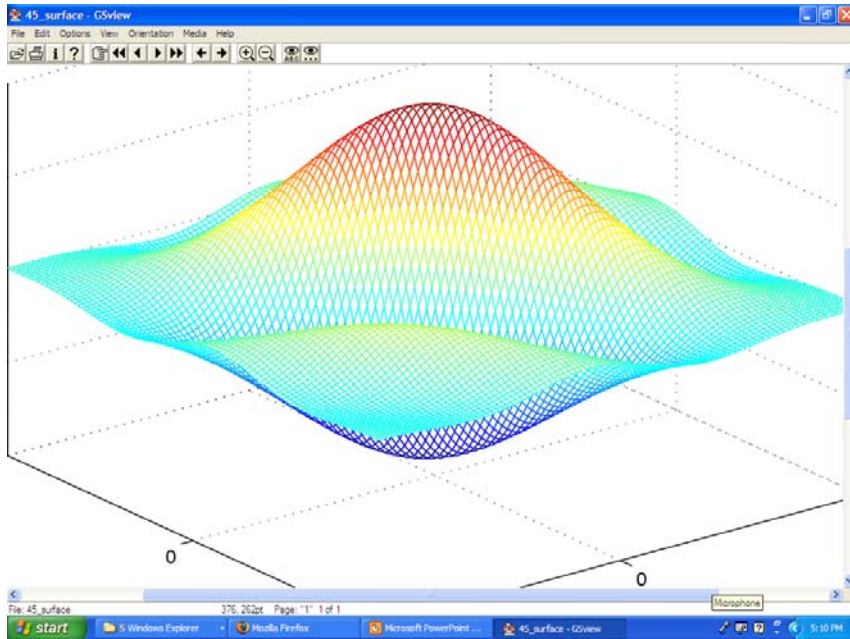
# Gabor Filters

- Similar approach to Laws
- Wavelets at different frequencies and different orientations

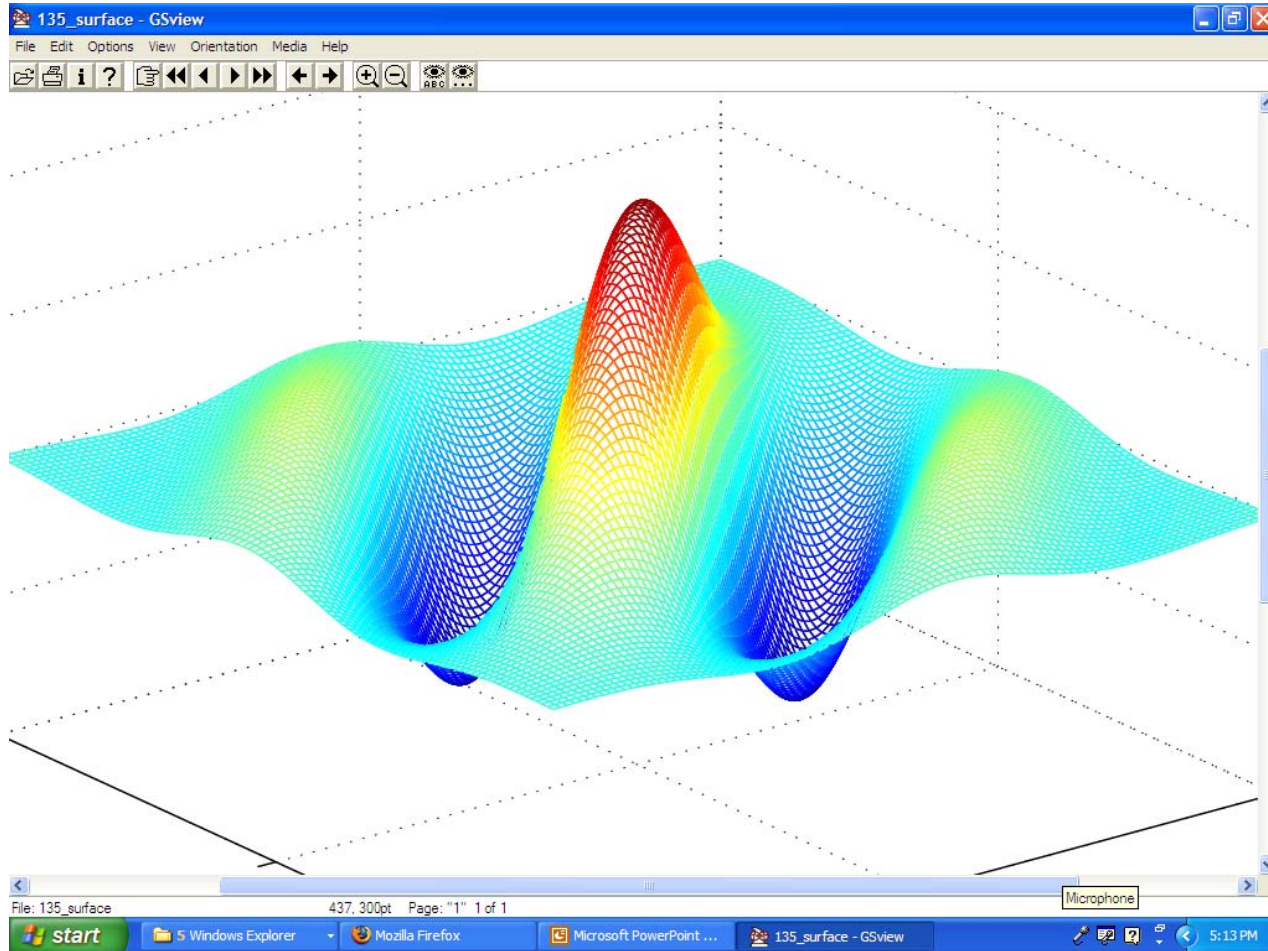




# Gabor Filters



# Gabor Filters



# Segmentation with Color and Gabor-Filter Texture (Smeulders)



A classical texture measure:

# Autocorrelation function

- Autocorrelation function can detect repetitive patterns of texels
- Also defines fineness/coarseness of the texture
- Compare the dot product (energy) of non shifted image with a shifted image

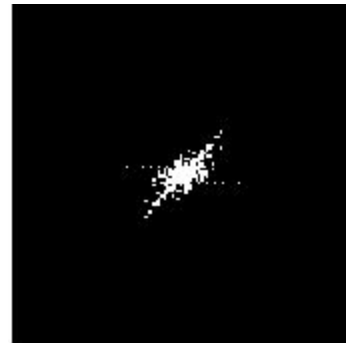
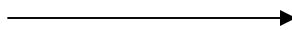
$$\begin{aligned}\rho(dr, dc) &= \frac{\sum_{r=0}^N \sum_{c=0}^N I[r,c]I(r+dr,c+dc)}{\sum_{r=0}^N \sum_{c=0}^N I^2[r,c]} \\ &= \frac{I[r,c] \circ I_d[r,c]}{I[r,c] \circ I[r,c]}\end{aligned}$$

# Interpreting autocorrelation

- Coarse texture  $\rightarrow$  function drops off slowly
- Fine texture  $\rightarrow$  function drops off rapidly
- Can drop differently for  $r$  and  $c$
- Regular textures  $\rightarrow$  function will have peaks and valleys; peaks can repeat far away from  $[0, 0]$
- Random textures  $\rightarrow$  only peak at  $[0, 0]$ ; breadth of peak gives the size of the texture

# Fourier power spectrum

- High frequency power  $\rightarrow$  fine texture
- Concentrated power  $\rightarrow$  regularity
- Directionality  $\rightarrow$  directional texture



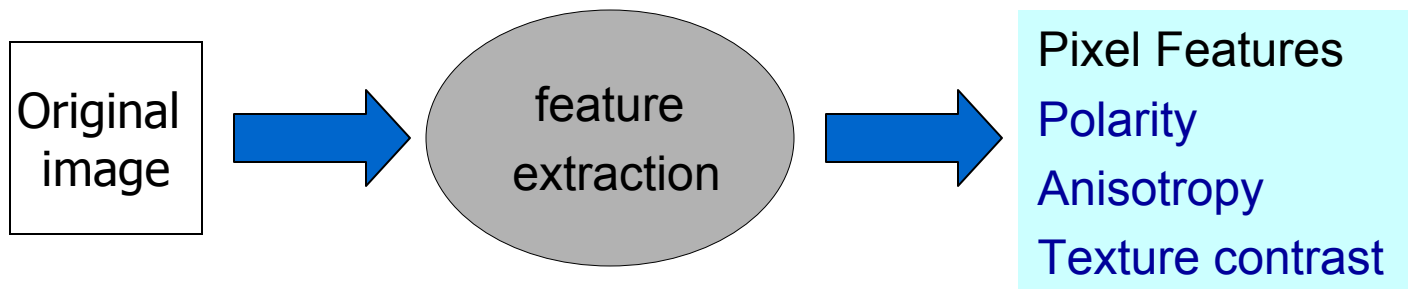
# Blobworld Texture Features

- Choose the best scale instead of using fixed scale(s)
- Used successfully in color/texture segmentation in Berkeley's Blobworld project



# Feature Extraction

- Input: image
- Output: pixel features
  - Color features
  - Texture features
  - Position features
- Algorithm: Select an appropriate scale for each pixel and extract features for that pixel at the selected scale





# Texture Scale

- Texture is a local neighborhood property.
- Texture features computed at a wrong scale can lead to confusion.
- Texture features should be computed at a scale which is appropriate to the local structure being described.



The white rectangles show some sample texture scales from the image.

# Scale Selection Terminology

- Gradient of the L\* component (assuming that the image is in the L\*a\*b\* color space) :  $\nabla I \begin{bmatrix} I_x \\ I_y \end{bmatrix}$
- Symmetric Gaussian :  $G_\sigma(x, y) = G_\sigma(x) * G_\sigma(y)$
- Second moment matrix:  $M_\sigma(x, y) = G_\sigma(x, y) * (\nabla I)(\nabla I)^T \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$

Notes:  $G_\sigma(x, y)$  is a separable approximation to a Gaussian.

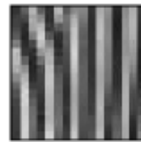
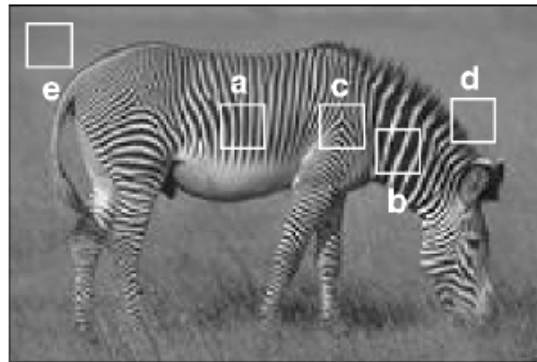
$\sigma$  is the standard deviation of the Gaussian [0, .5, ... 3.5].

$\sigma$  controls the size of the window around each pixel [1 2 5 10 17 26 37 50].

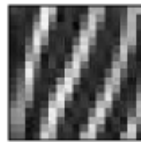
$M_\sigma(x, y)$  is a 2X2 matrix and is computed at different scales defined by  $\sigma$ .

# Scale Selection (continued)

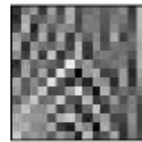
- Make use of polarity (a measure of the extent to which the gradient vectors in a certain neighborhood all point in the same direction) to select the scale at which  $M_\sigma$  is computed



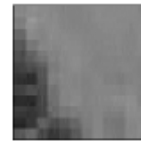
(a)



(b)



(c)



(d)



(e)

Edge: polarity is close to 1 for all scales  $\sigma$   
Texture: polarity varies with  $\sigma$   
Uniform: polarity takes on arbitrary values

# Scale Selection (continued)

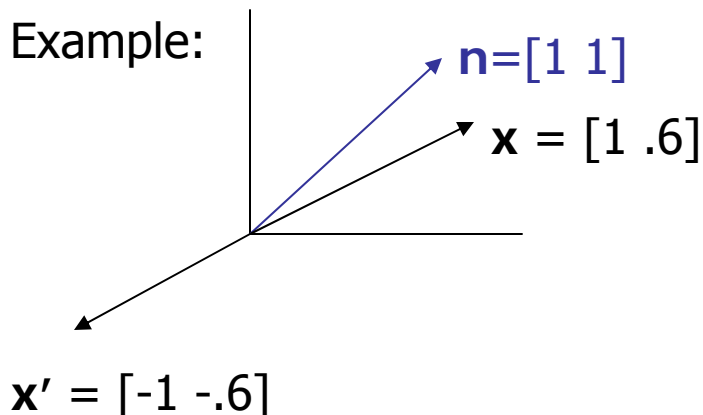
polarity  $p_\sigma$

$$p_\sigma = \frac{|E_+ - E_-|}{E_+ + E_-}$$

$$E_+ = \sum_{x,y} G_\sigma(x,y) [\nabla I \cdot \hat{n}]_+$$

$$E_- = \sum_{x,y} G_\sigma(x,y) [\nabla I \cdot \hat{n}]_-$$

- $\mathbf{n}$  is a unit vector perpendicular to the dominant orientation.
- The notation  $[x]_+$  means  $x$  if  $x > 0$  else 0  
The notation  $[x]_-$  means  $x$  if  $x < 0$  else 0
- We can think of  $E^+$  and  $E^-$  as measures of how many gradient vectors in the window are on the positive side and how many are on the negative side of the dominant orientation in the window.



# Scale Selection (continued)

- Texture scale selection is based on the derivative of the polarity with respect to scale  $\sigma$ .
- Algorithm:
  1. Compute polarity at every pixel in the image for  $\sigma_k = k/2$ , ( $k = 0, 1 \dots 7$ ).
  2. Convolve each polarity image with a Gaussian with standard deviation  $2k$  to obtain a smoothed polarity image.
  3. For each pixel, the selected scale is the first value of  $\sigma$  for which the difference between values of polarity at successive scales is less than 2 percent.

# Texture Features Extraction

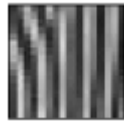
- Extract the texture features at the selected scale

- **Polarity** (polarity at the selected scale) :  $p = p_{\sigma^*}$

- **Anisotropy** :  $a = 1 - \lambda_2 / \lambda_1$

$\lambda_1$  and  $\lambda_2$  denote the eigenvalues of  $M_{\sigma}$

$\lambda_2 / \lambda_1$  measures the degree of orientation: when  $\lambda_1$  is large compared to  $\lambda_2$  the local neighborhood possesses a dominant orientation. When they are close, no dominant orientation. When they are small, the local neighborhood is constant.



- **Local Contrast**:  $C = 2(\lambda_1 + \lambda_2)^{3/2}$

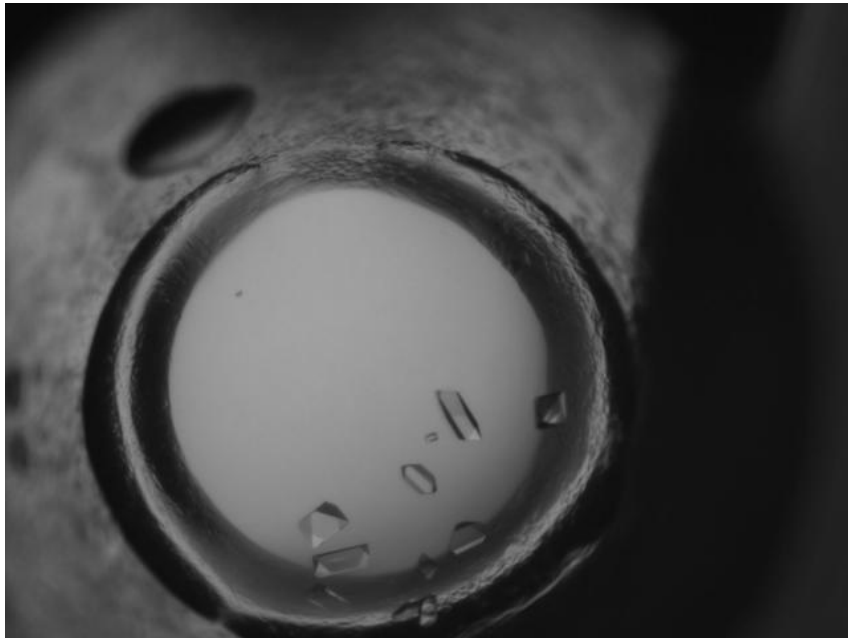
A pixel is considered homogeneous if  $\lambda_1 + \lambda_2 <$  a local threshold

# Blobworld Segmentation Using Color and Texture





# Application to Protein Crystal Images



Original image in PGM (Portable Gray Map )  
format

- K-mean clustering result (number of clusters is equal to 10 and similarity measure is Euclidean distance)
- Different colors represent different textures



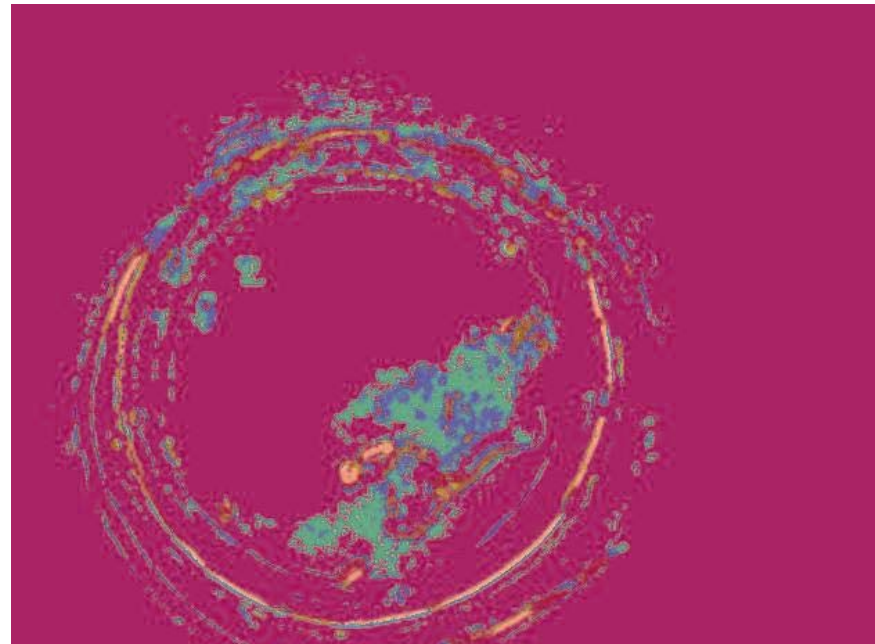


# Application to Protein Crystal Images



Original image in PGM (Portable Gray Map )  
format

- K-mean clustering result (number of clusters is equal to 10 and similarity measure is Euclidean distance)
- Different colors represent different textures



# References

- Chad Carson, Serge Belongie, Hayit Greenspan, and Jitendra Malik. "Blobworld: Image Segmentation Using Expectation-Maximization and Its Application to Image Querying." IEEE Transactions on Pattern Analysis and Machine Intelligence 2002; Vol 24. pp. 1026-38.
- W. Forstner, "A Framework for Low Level Feature Extraction," Proc. European Conf. Computer Vision, pp. 383-394, 1994.