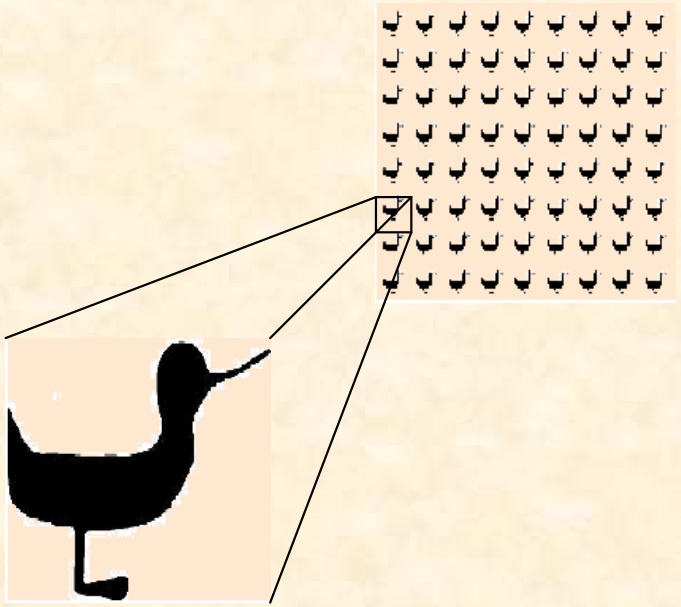
TEXTURE ANALYSIS

USING

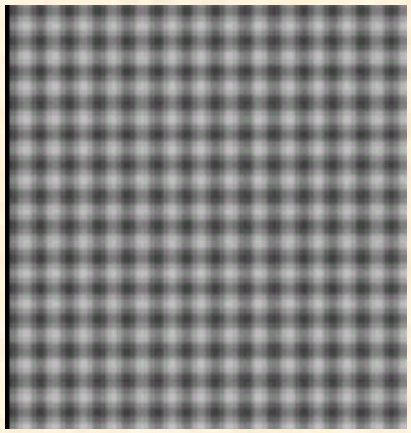
GABOR FILTERS

Texture Types

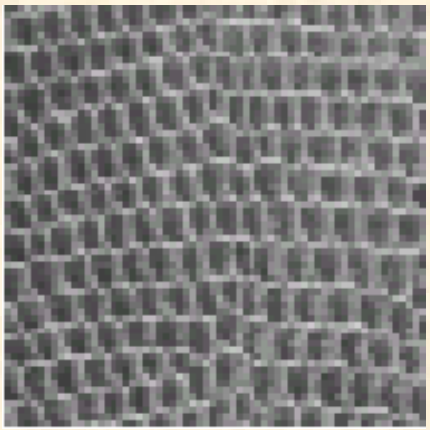
- Definition of Texture



- Texture types



Synthetic



Natural

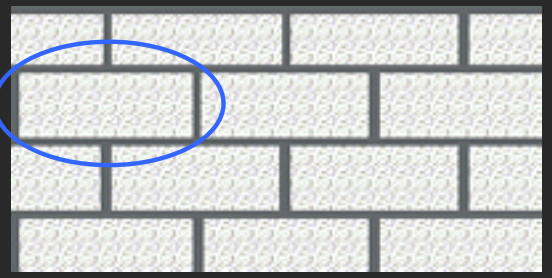
Stochastic

< Prev

Next >

Texture Definition

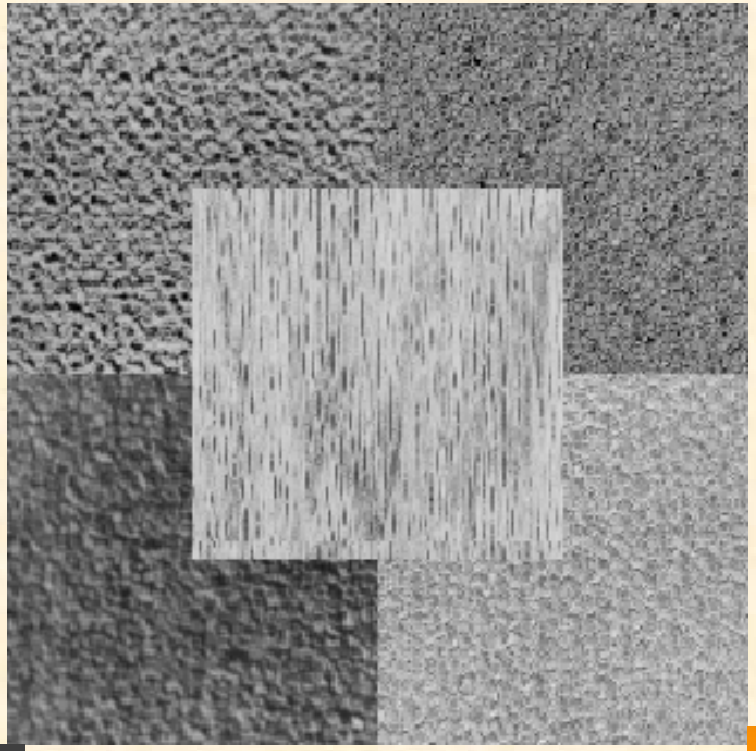
Texture: the regular repetition of an element or pattern on a surface.

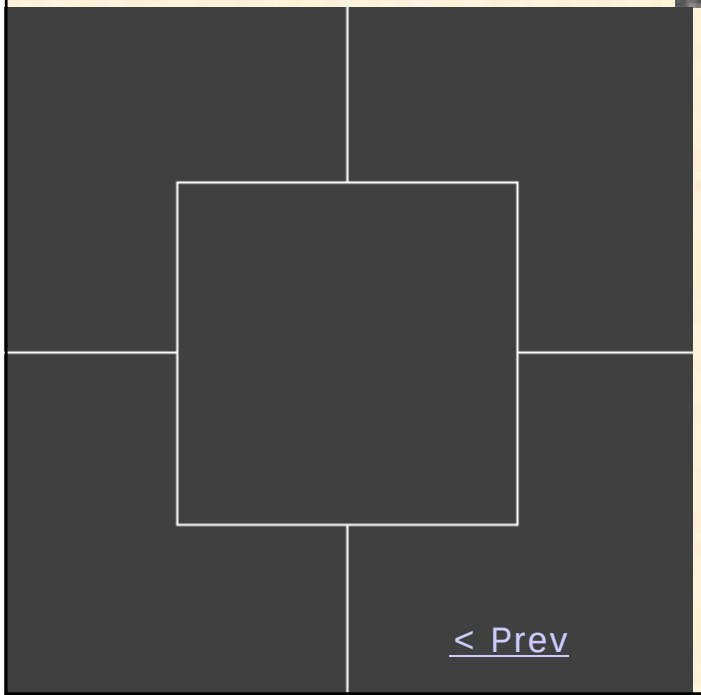


- Purpose of texture analysis:
  - **To identify different textured and non-textured regions in an image.**
  - ***To classify/segment different texture regions in an image.***
  - ***To extract boundaries between major texture regions.***
  - **To describe the texel unit.**
  - **3-D shape from texture**

Ref: [Forsyth2003, Raghu95]

Texture Regions & Edges





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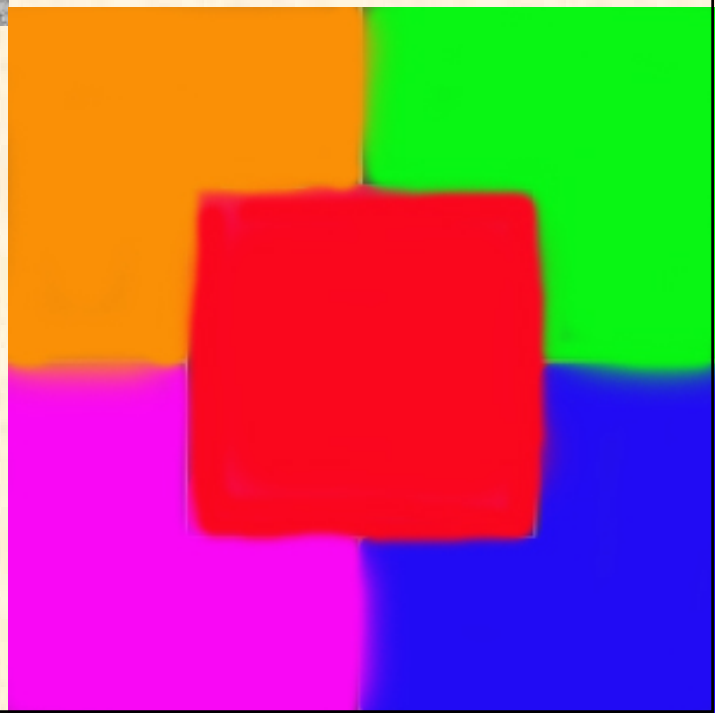
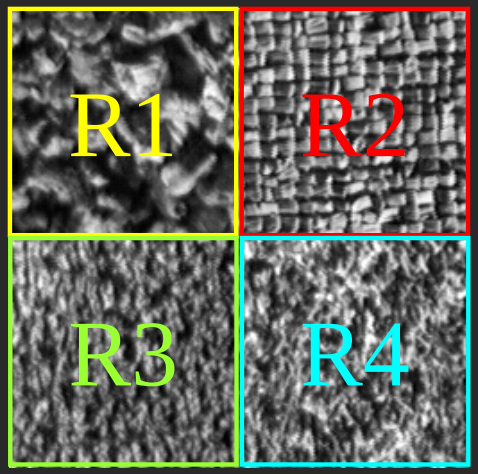
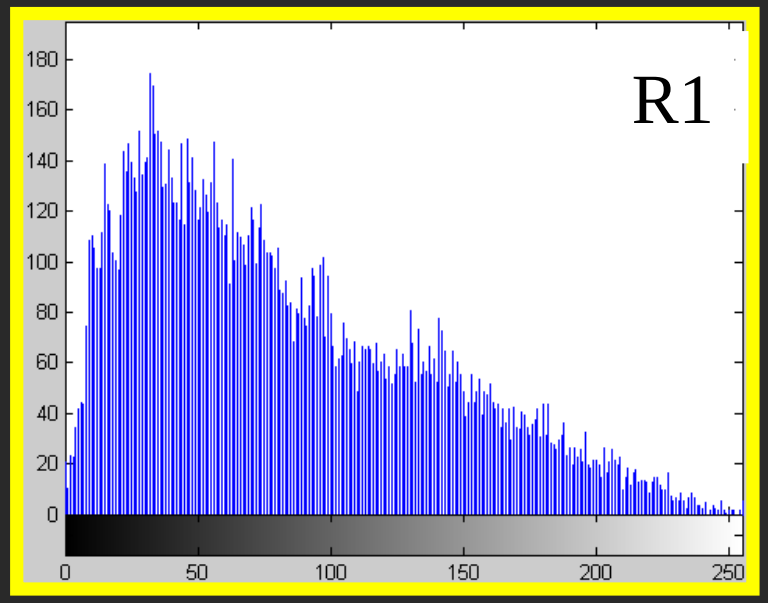
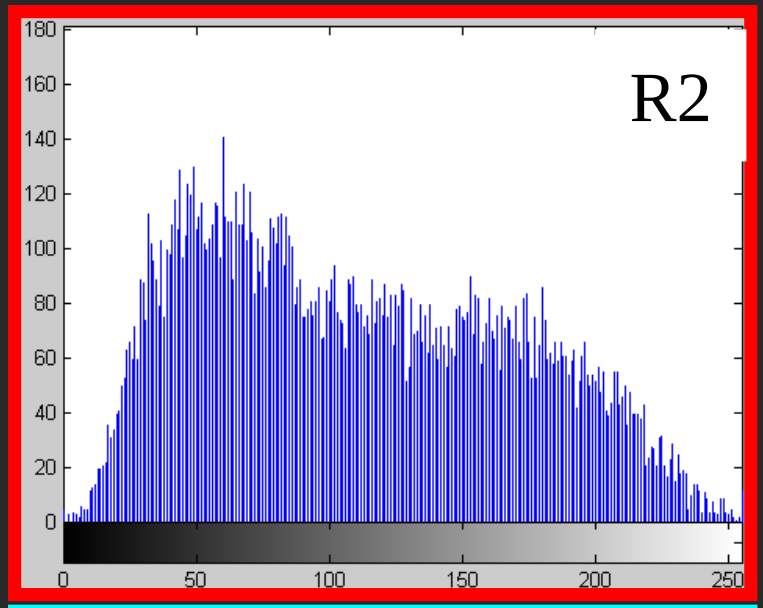
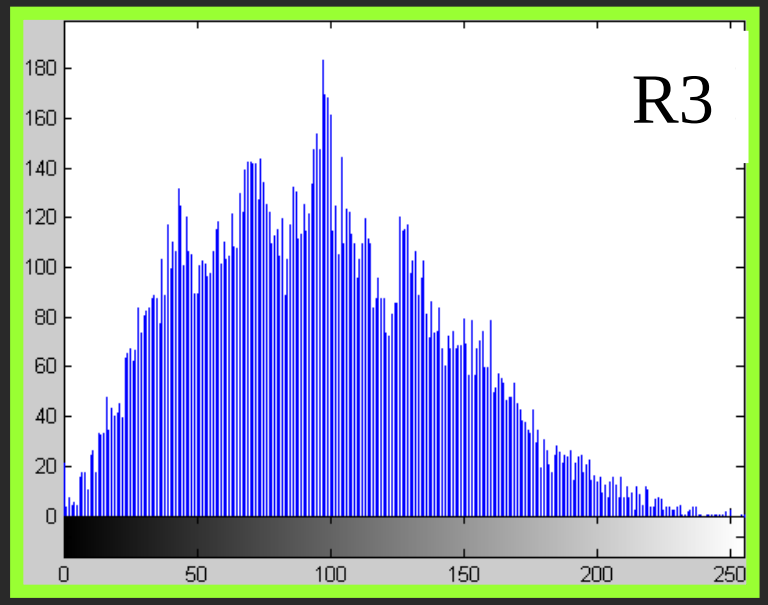




Textured image







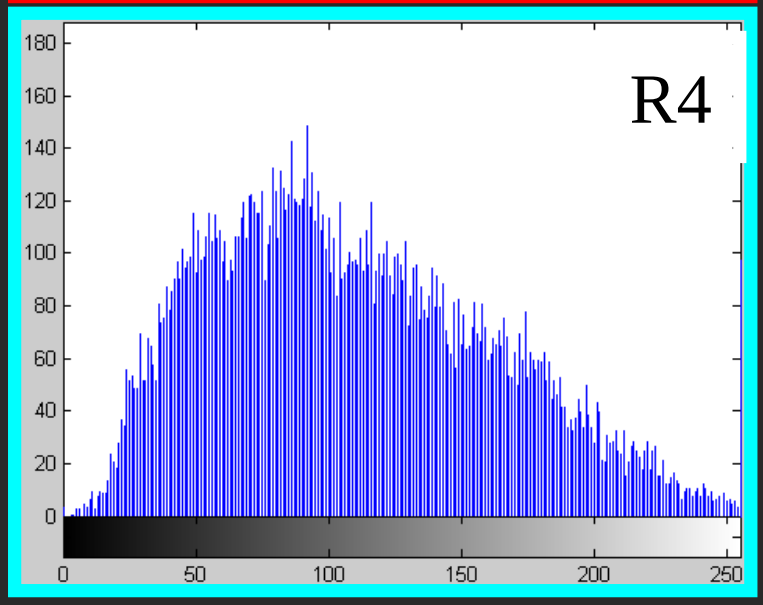
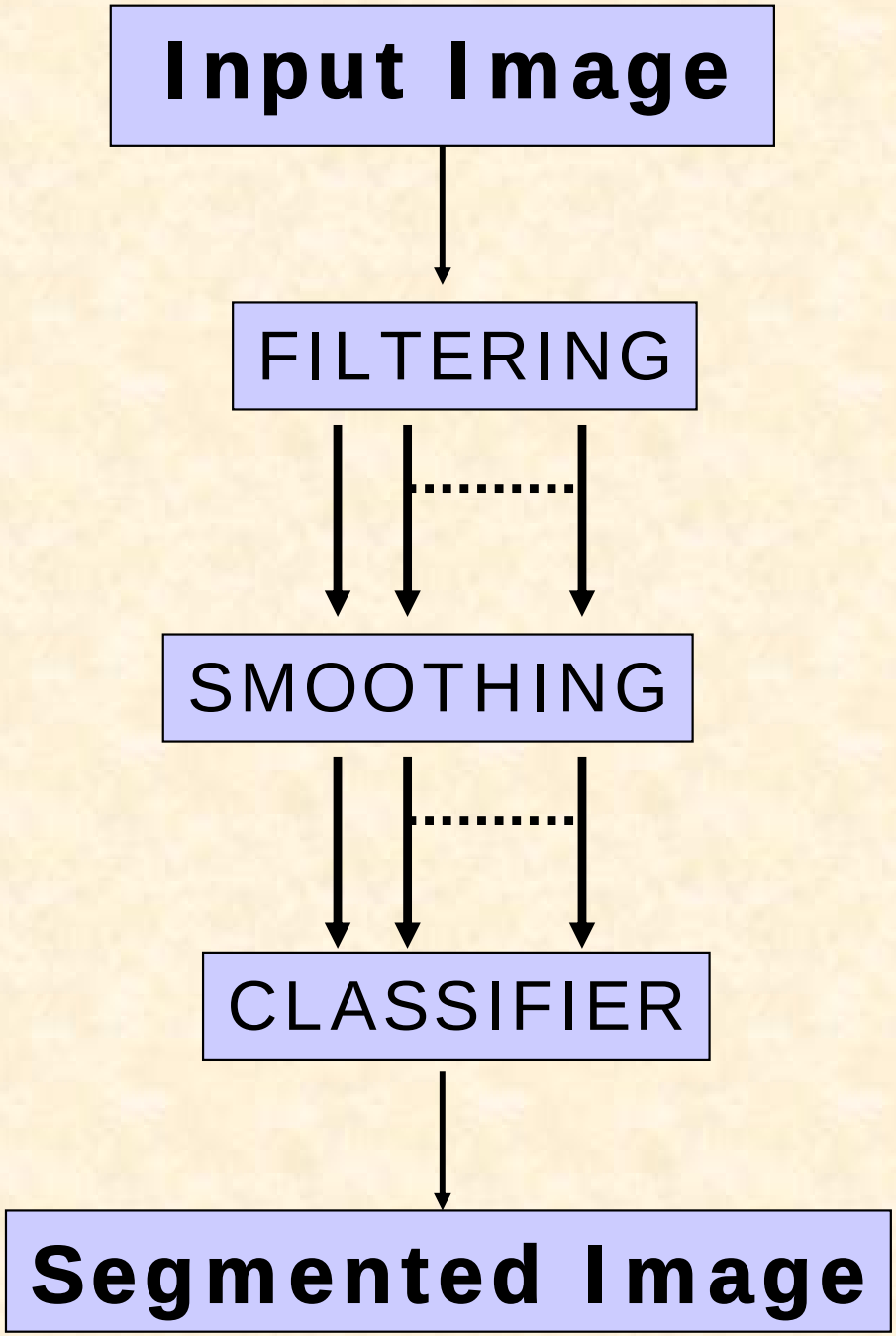
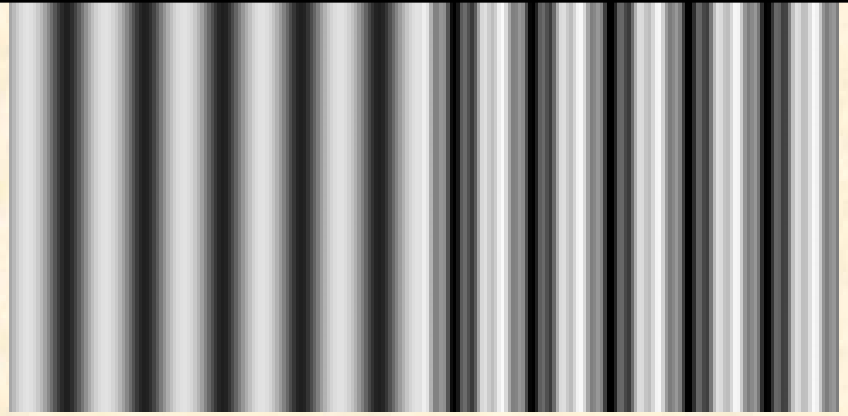


Image histograms

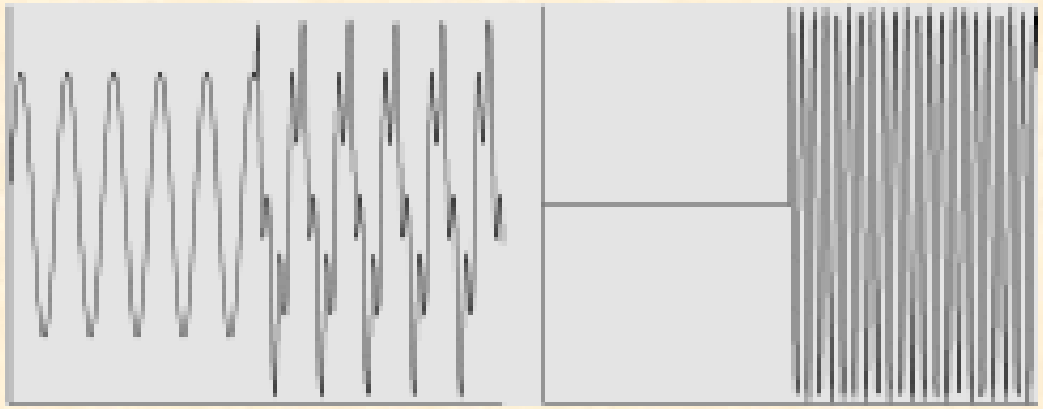


Flow-chart of a typical method of texture classification



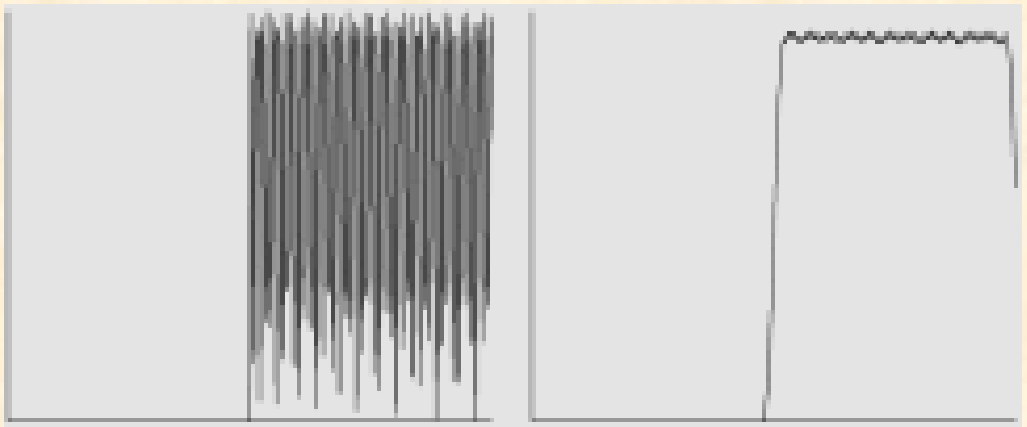
Synthetic Texture Image

Horizontal intensity profile

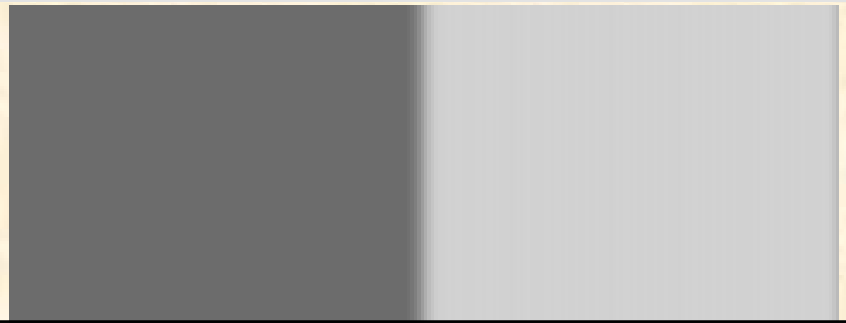


Filtered output

Nonlinear transform



Smoothing

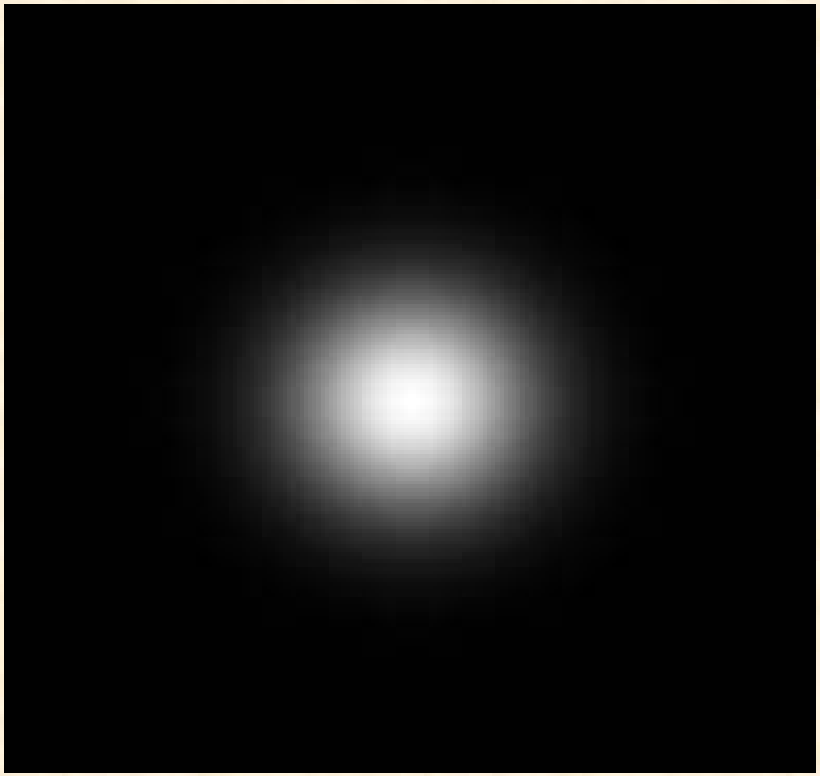


Segmented image

Processing of Texture-like Images

2-D Gabor Filter

$$f(x, y, \omega, \theta, \sigma_x, \sigma_y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left[\frac{-1}{2}\left(\left(\frac{x}{\sigma_x}\right)^2 + \left(\frac{y}{\sigma_y}\right)^2\right) + j\omega(x\cos\theta + y\sin\theta)\right]$$

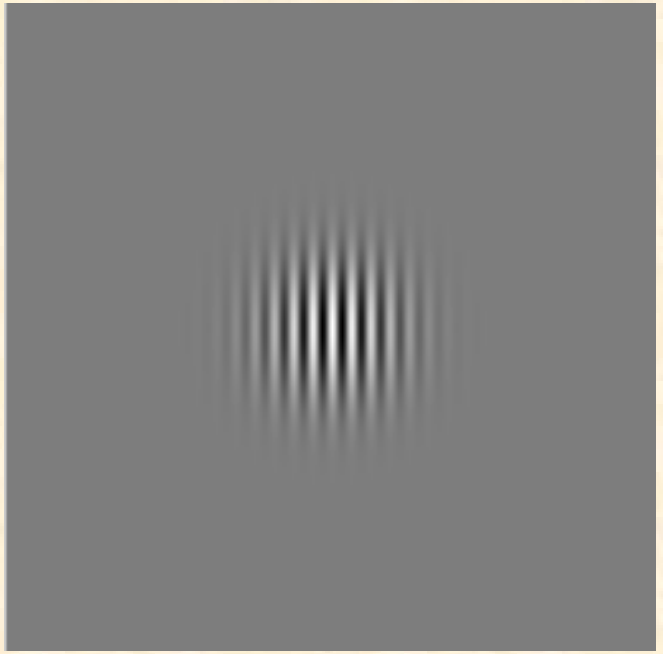


A typical Gaussian filter with σ=30

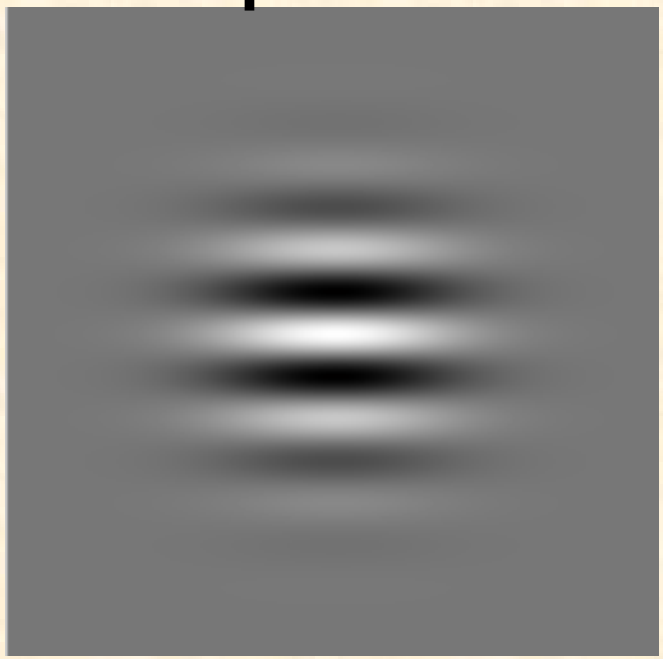
A typical Gabor filter with σ=30, ω=3.14 and θ=45°

< Prev

Next >



Gabor filters with different combinations of spatial width σ, frequency ω and orientation θ.



2-D Gabor filter:

$$f(x, y, \omega, \theta, \sigma_x, \sigma_y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left[\frac{-1}{2}\left(\left(\frac{x}{\sigma_x}\right)^2 + \left(\frac{y}{\sigma_y}\right)^2\right) + j\omega(x\cos\theta + y\sin\theta)\right]$$

where

σ	is the spatial spread
ω	is the frequency
θ	is the orientation

1-D Gabor filter:

$$f(x, \omega, \sigma) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(\frac{-x^2}{2\sigma^2} + j\omega x\right)$$

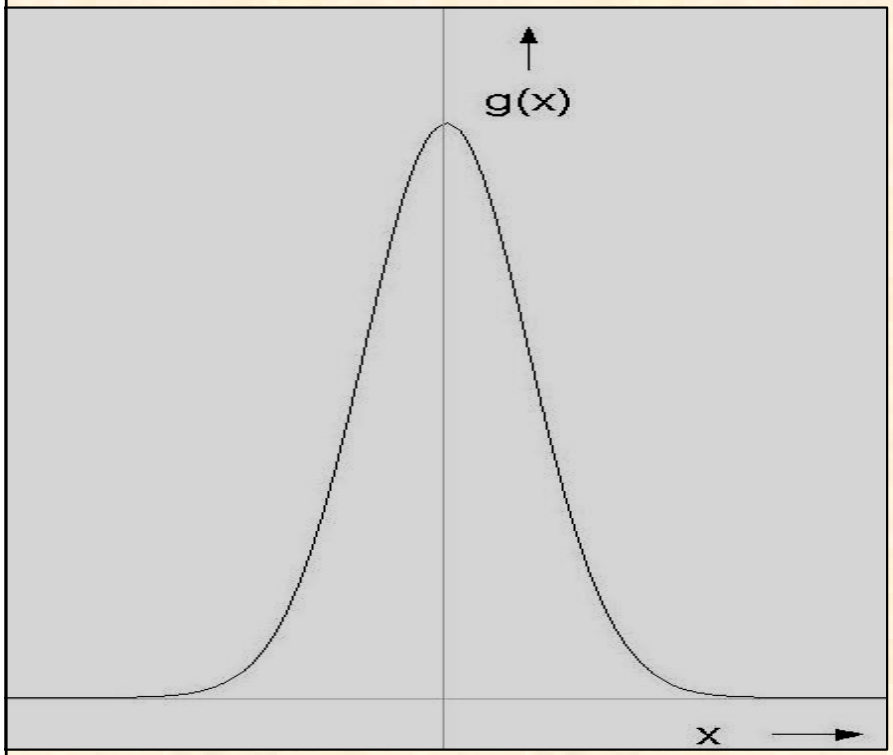
1-D Gaussian function:

$$g(x) = \frac{1}{\sqrt{2\pi}\sigma_1}\exp\left(\frac{-x^2}{2\sigma^2}\right)$$

Processing of Texture-like Images

1-D Gaussian Filter

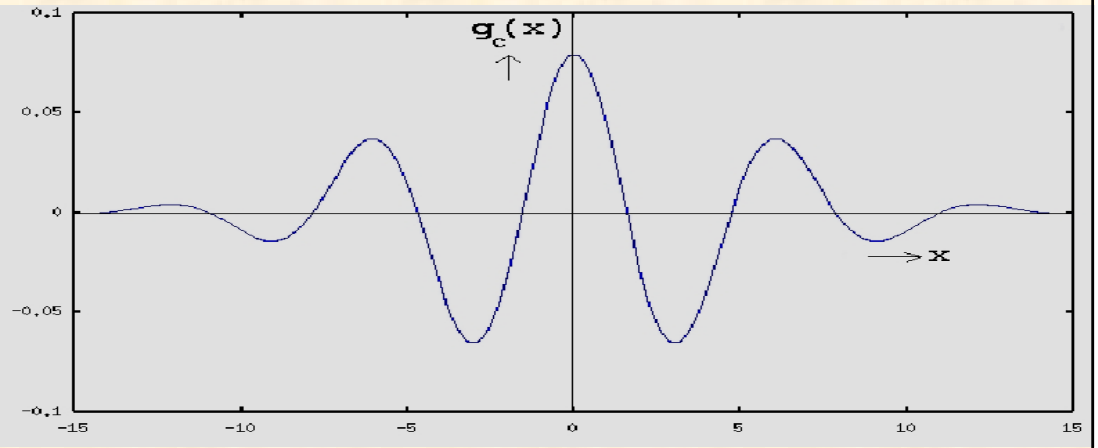
$$g(x) = \frac{1}{\sqrt{2\pi}\sigma_1} \exp\left(\frac{-x^2}{2\sigma^2}\right)$$



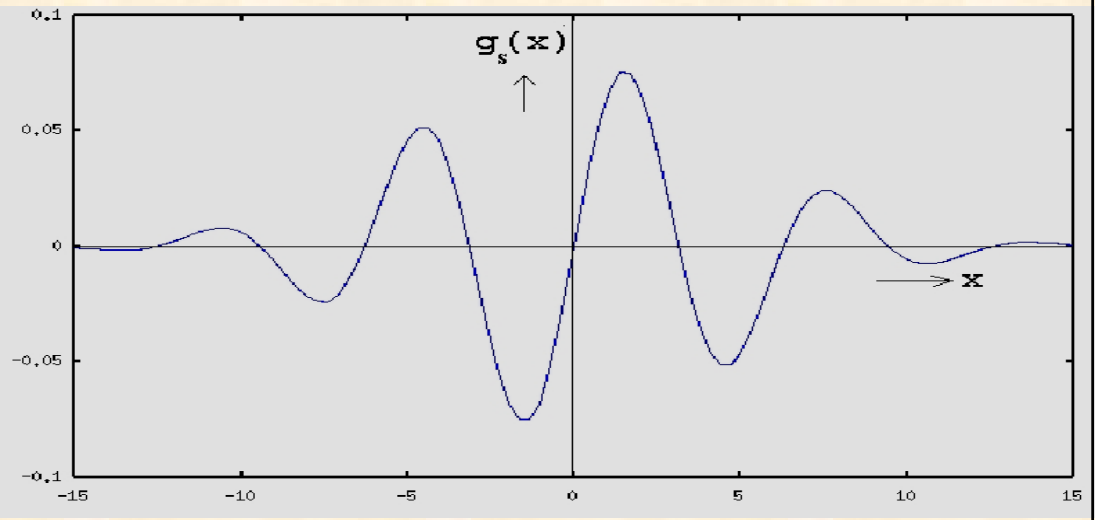
1-D Gabor Filter

$$f(x,\omega,\sigma) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(\frac{-x^2}{2\sigma^2} + j\omega x\right)$$

Even Component



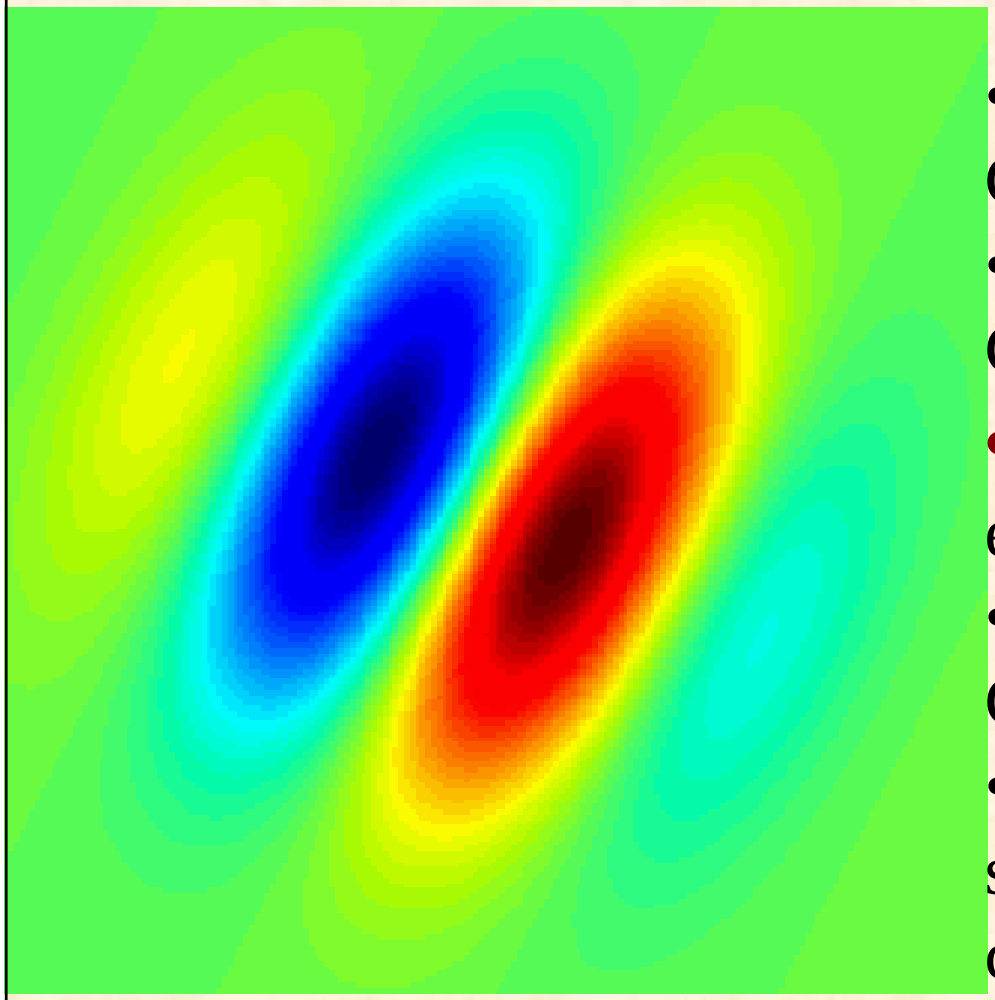
Odd Component



< Prev

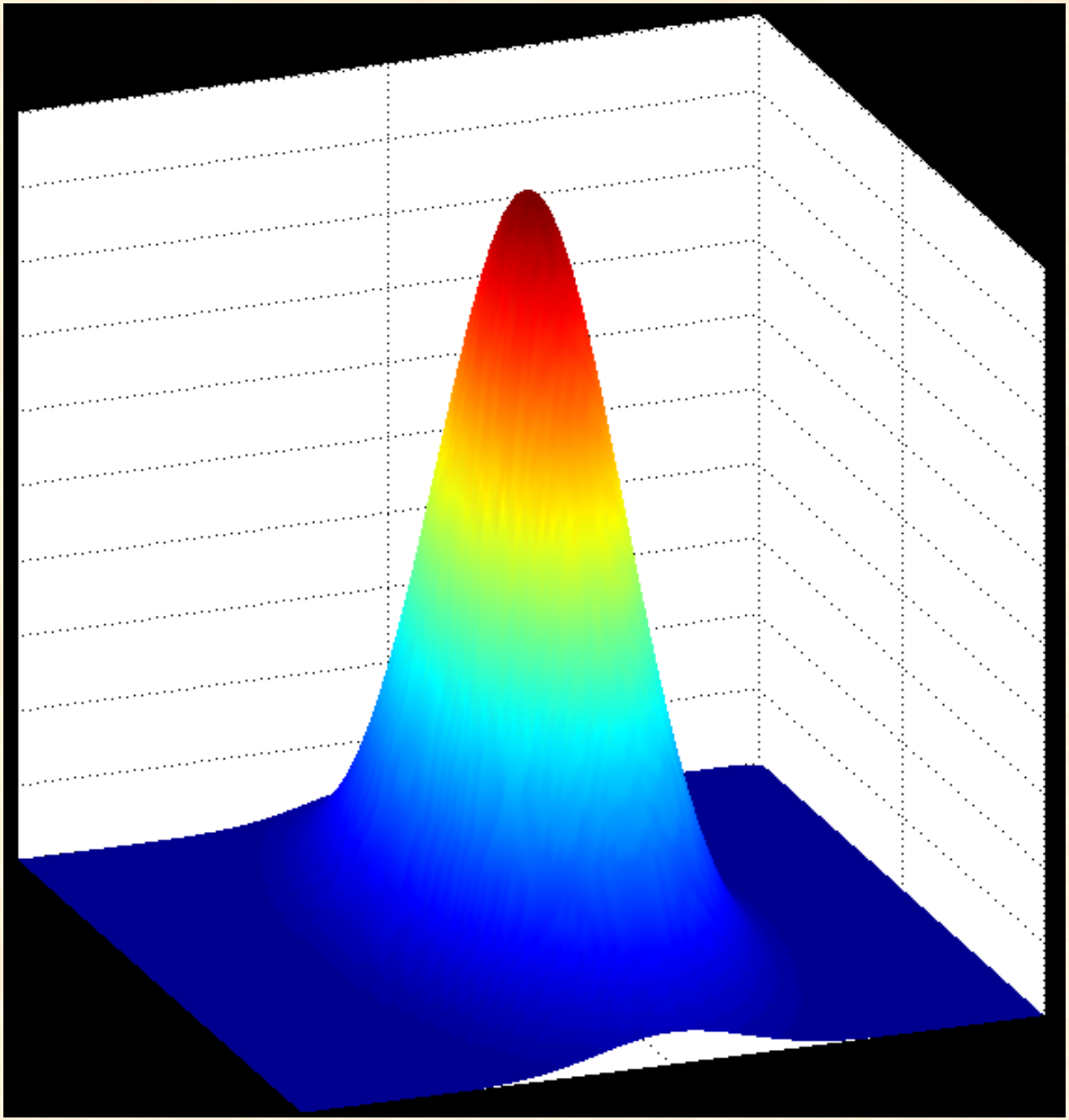
Next >

$$g(x,y) = K\exp(-\pi(a^2(x-x_0)_\theta^2 + b^2(y-y_0)_\theta^2))$$
$$\exp(j(2\pi F_0(x\cos\omega_0 + y\sin\omega_0) + P)$$

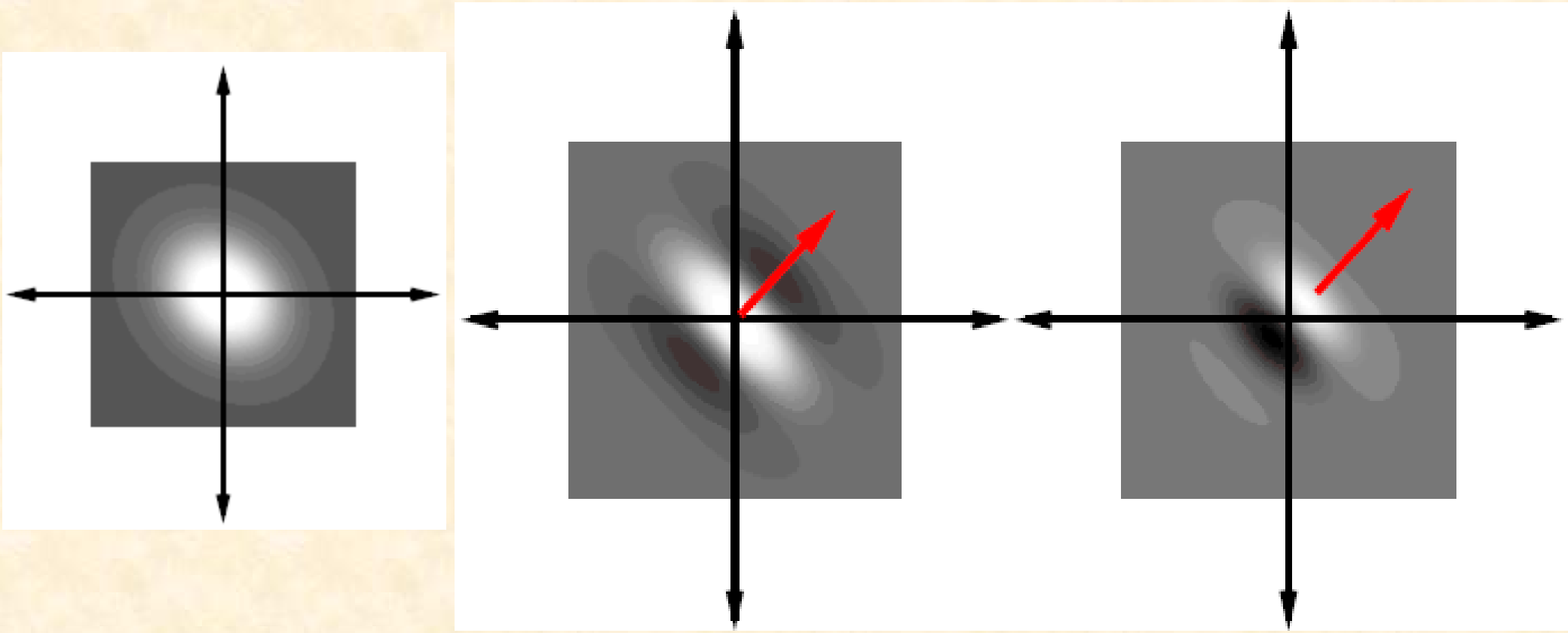


- **K** : Scales the magnitude of the Gaussian envelop.
- **(a, b)** : Scale the two axis of the Gaussian envelop.
- **θ** : (Rotation) angle of the Gaussian envelop.
- **(x_0, y_0)** : Location of the peak of the Gaussian envelop.
- **(u_0, v_0)** : Spatial frequencies of the sinusoidal carrier in Cartesian coordinates. It can also be expressed in polar coordinates as **(F_0, ω_0).**
- **P** : Phase of the sinusoidal carrier.

$$g(x,y) =$$
$$K\exp(-\pi(a^2(x-x_0)_\theta^2 + b^2(y-y_0)_\theta^2) + j(2\pi(u_0x + v_0y) + P)$$



Asymmetric 2-D Gaussian function



Asymmetrical Gaussian of 128×128 pixels. The parameters are as follows:

$x_0 = y_0 = 0$; **a = 1/50 pixels; b = 1/40 pixels;** $\theta = -45$ **deg.**

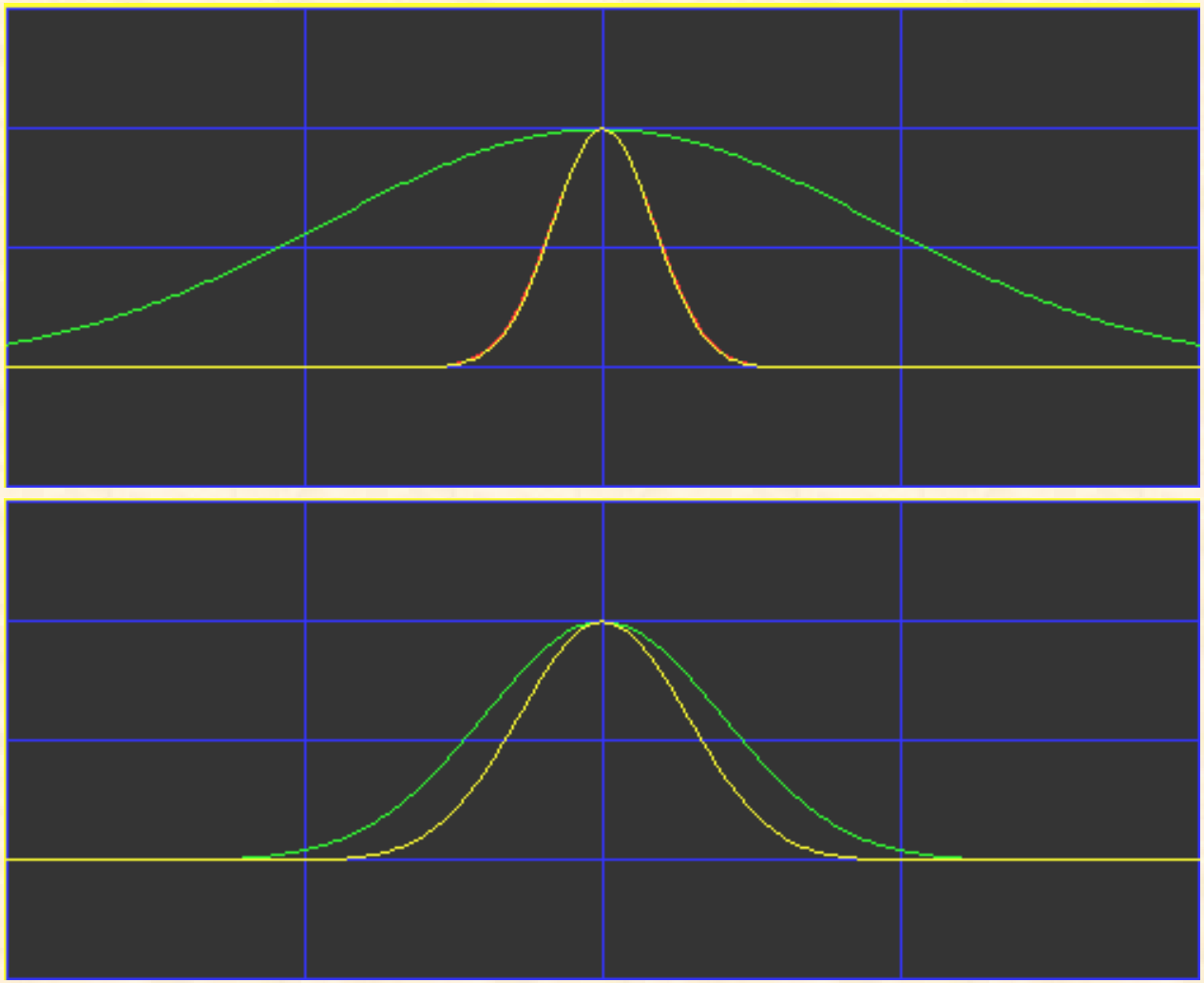
The real and imaginary parts of a complex Gabor function in space domain, with

F_0 = sqrt(2)/80 cycles/pixel, ω_0 = 45 deg, P = 0 deg.

Gaussian and its integral

$$\int_{-\infty}^{\infty} e^{-x^2}\,dx = \sqrt{\pi}$$

$$\int_{-\infty}^{\infty} ae^{-\frac{(x-b)^2}{2c^2}}\,dx = ac\cdot\sqrt{2\pi}.$$



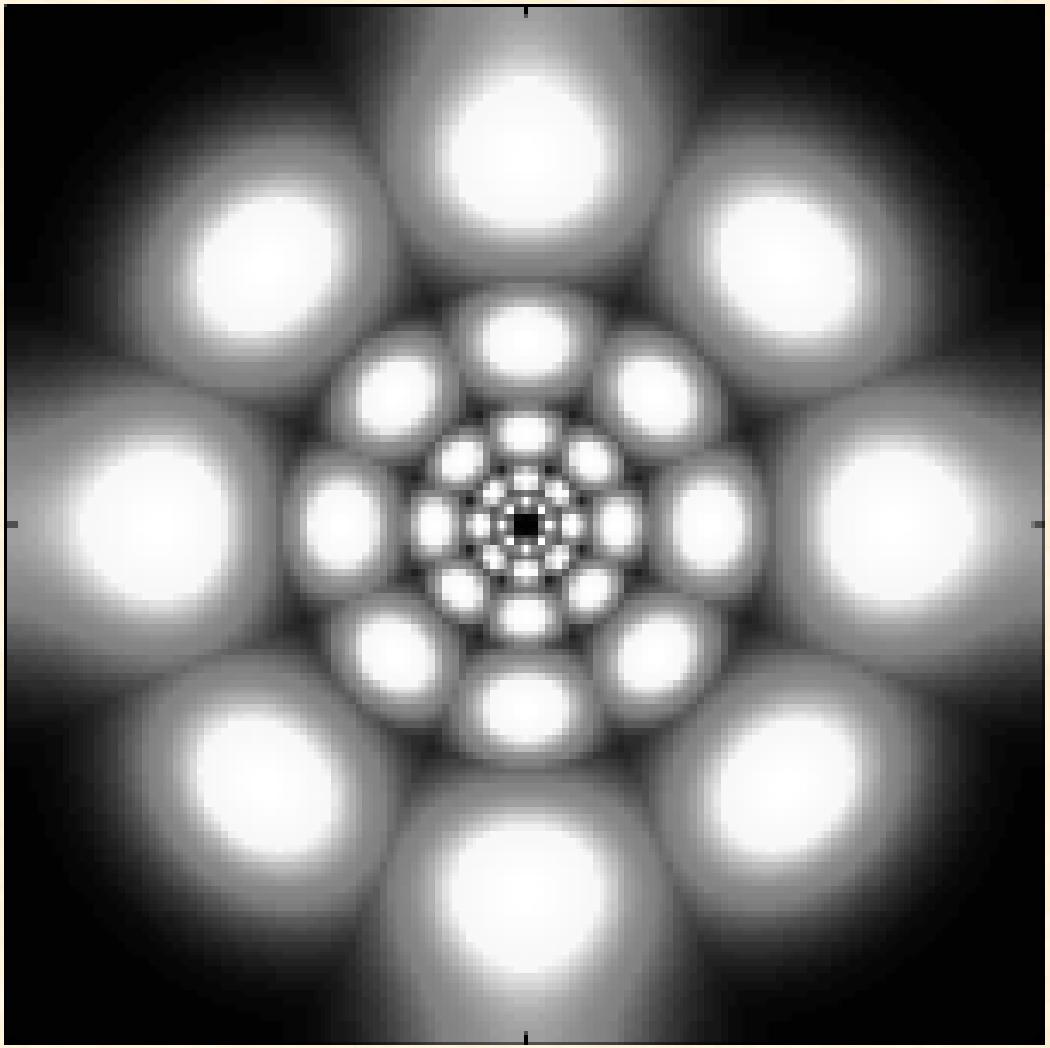
Fourier transform of the Gaussian

$$f(x) = e^{-t^2/a}$$

$$F(\omega) =$$

$$(\sqrt{a\pi})e^{-a\omega^2/4}$$

Fourier transform of the GABOR ??

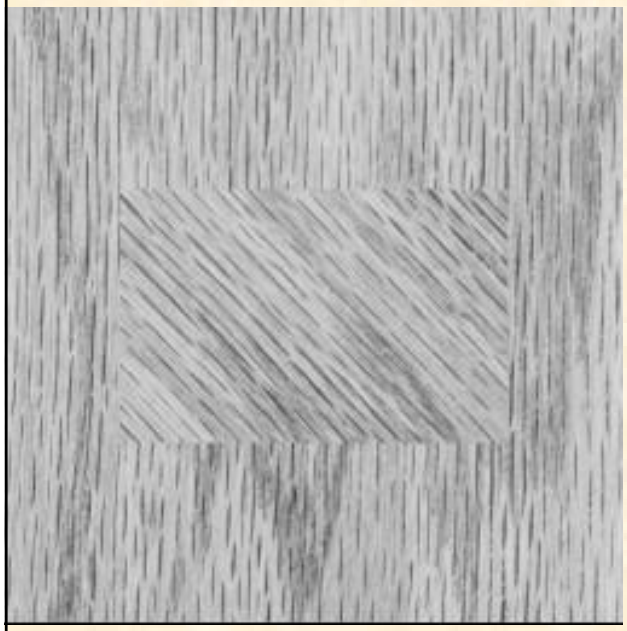


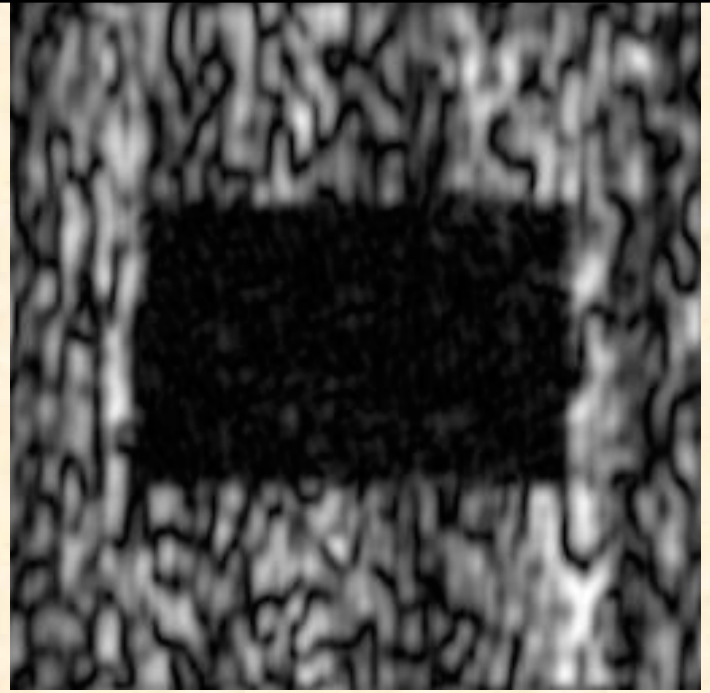
The frequency response of a typical *dyadic* bank of Gabor filters. One center-symmetric pair of lobes in the illustration represents each filter.

Some properties of Gabor filters:

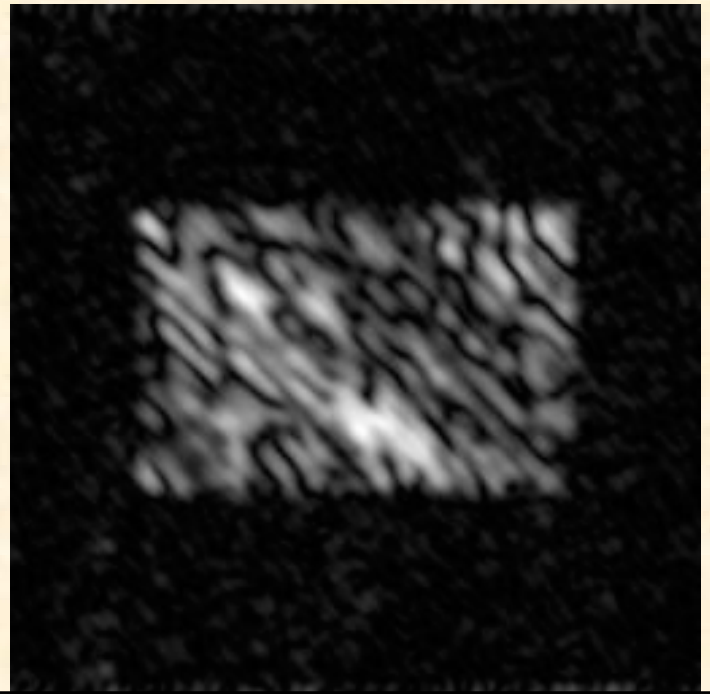
- **A tunable bandpass filter**
- **Similar to a STFT or windowed Fourier transform**
- **Satisfies the lower-most bound of the time-spectrum resolution (uncertainty principle)**
- **It's a multi-scale, multi-resolution filter**
- **Has selectivity for orientation, spectral bandwidth and spatial extent.**
- **Has response similar to that of the Human visual cortex (first few layers of brain cells)**
- **Used in many applications – texture segmentation; iris, face and fingerprint recognition.**
- **Computational cost often high, due to the necessity of using a large bank of filters in most applications**

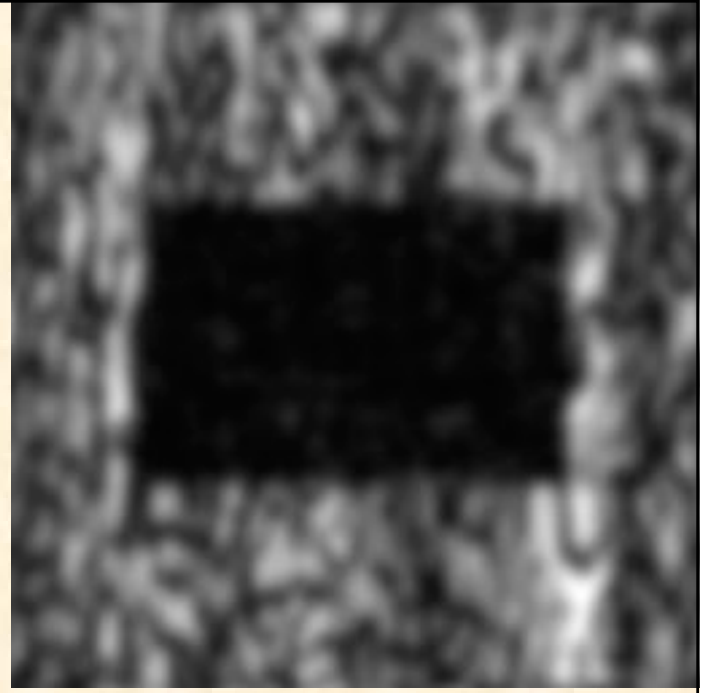
Texture Image



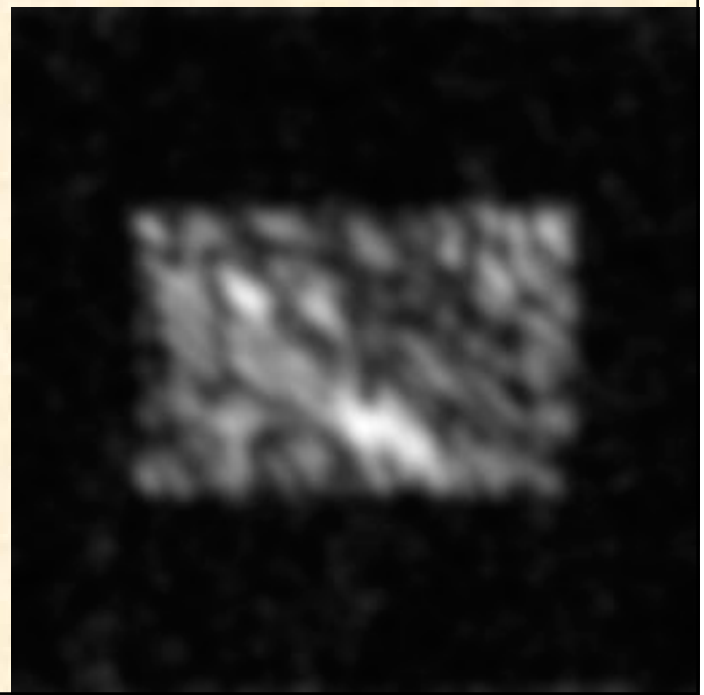


Magnitude of the Gabor Responses

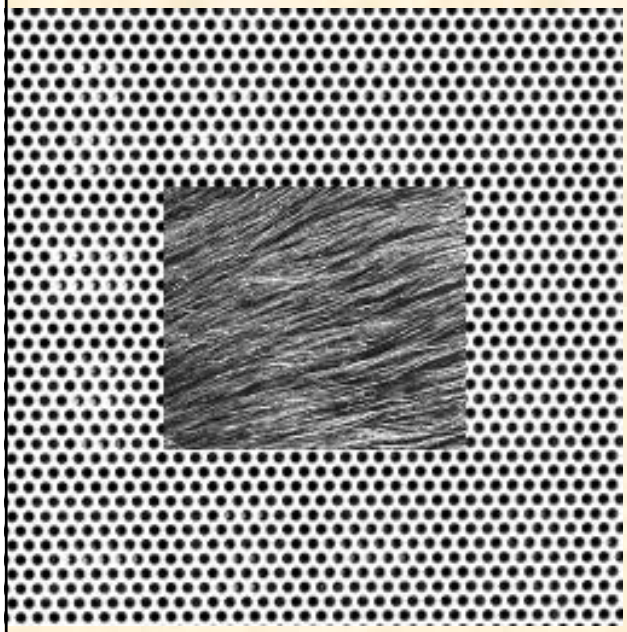


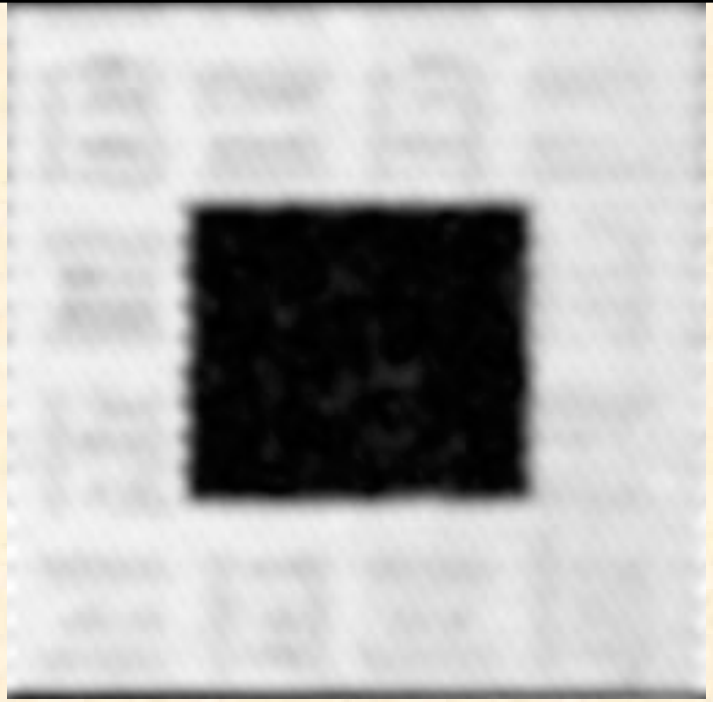


Smoothed Features

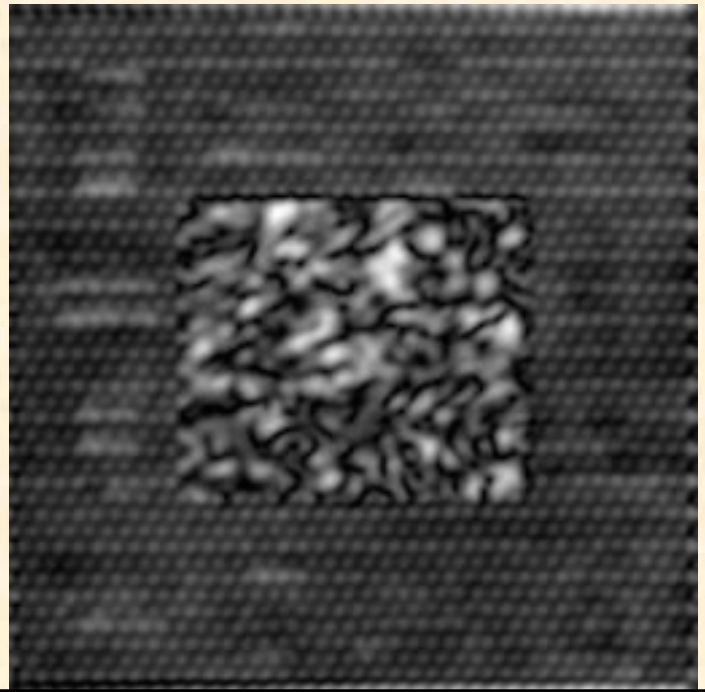


Texture Image



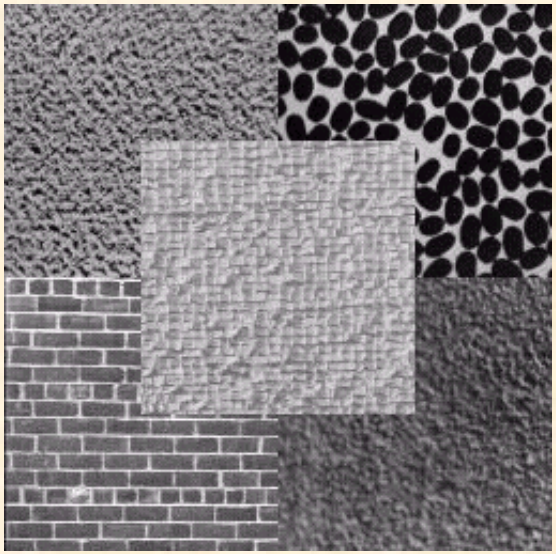


Magnitude of the Gabor Responses

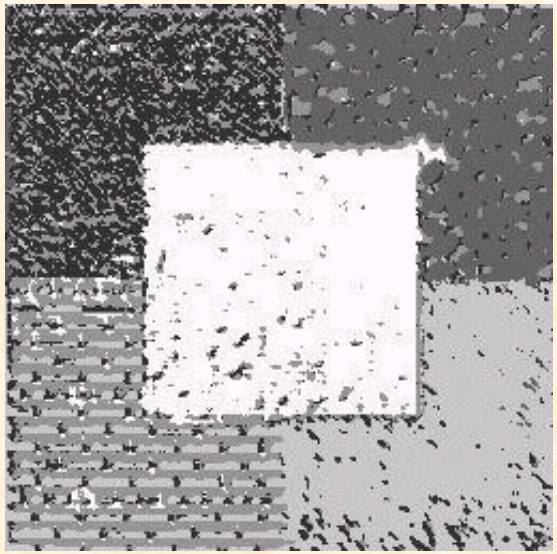


Smoothed Features

Natural Textures



Initial Classification



Final Classification

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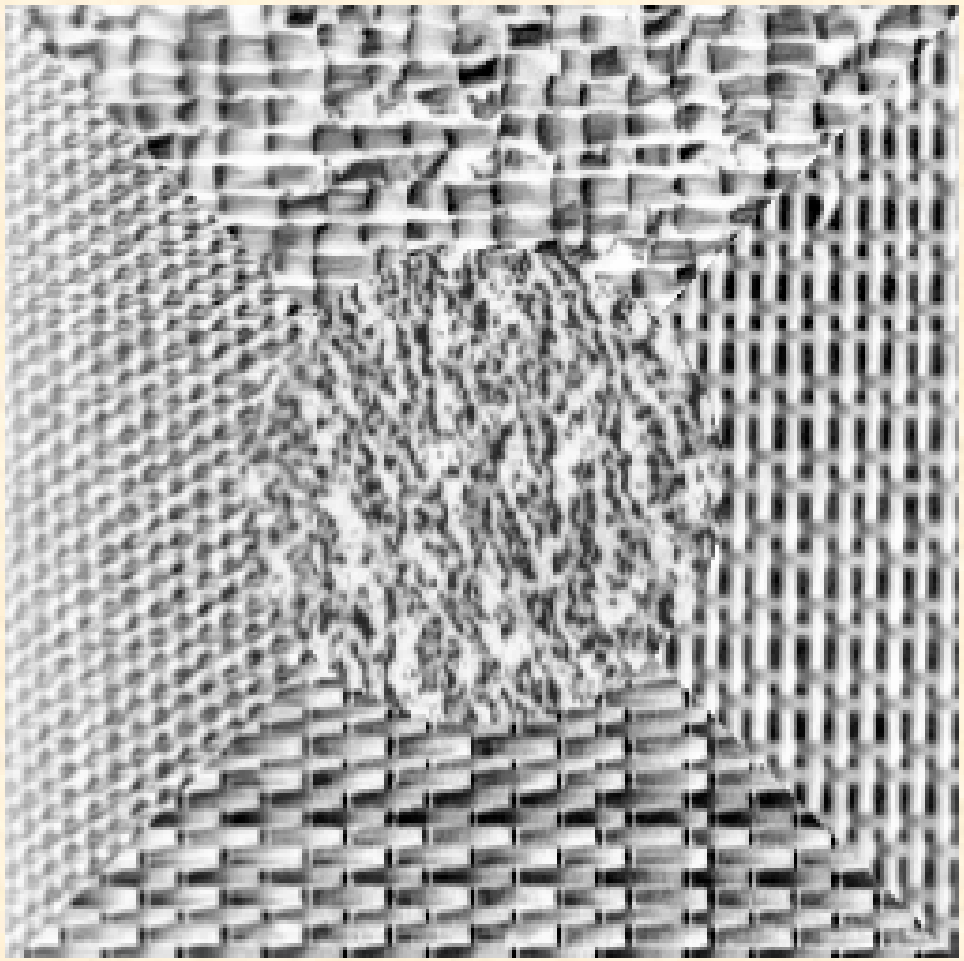
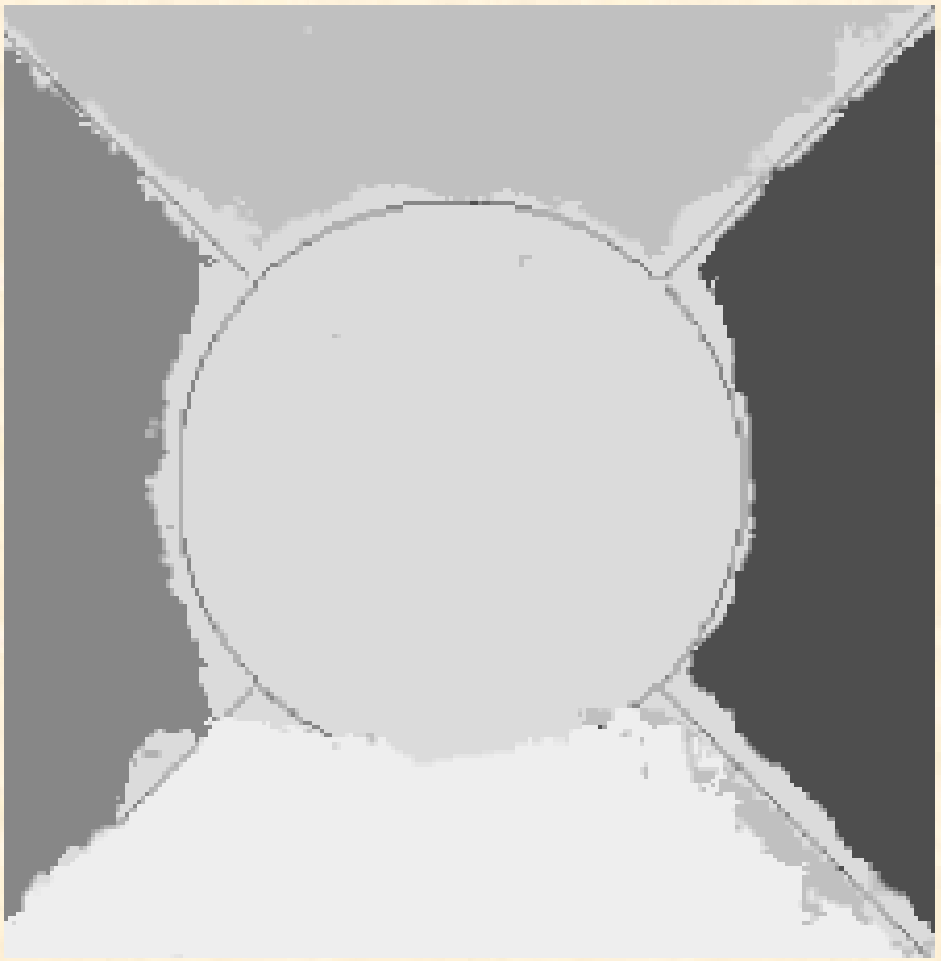
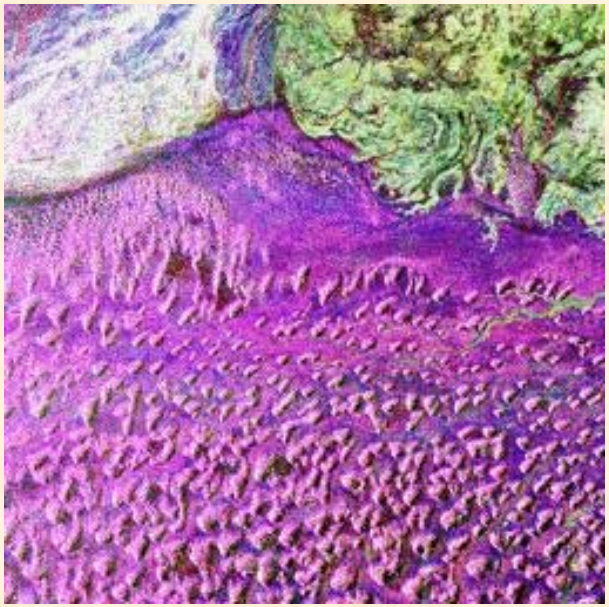


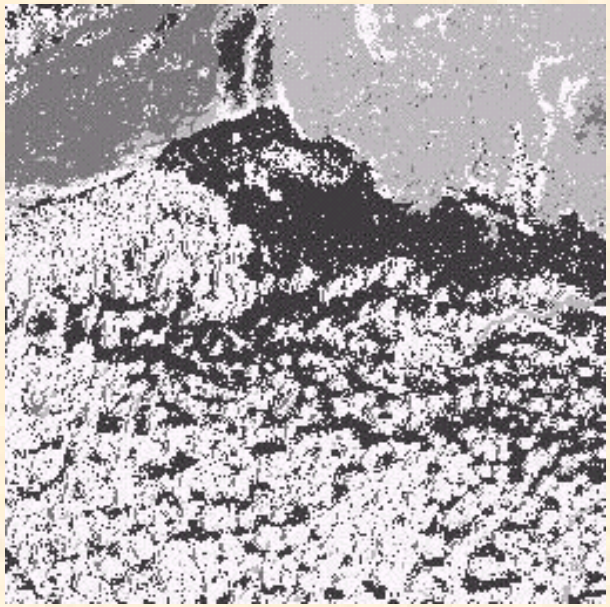


Segmentation using Gabor based features of a texture image containing five regions.

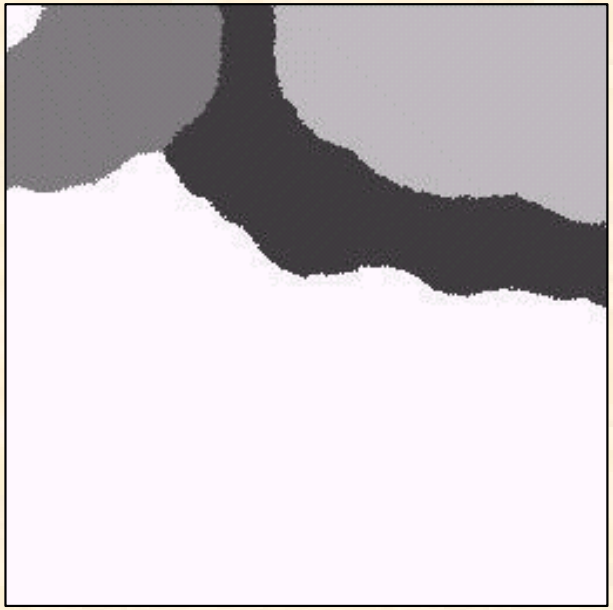
SIR-C/X-SAR image of Lost City of Ubar



Classification using multispectral information



Classification using multispectral and textural information



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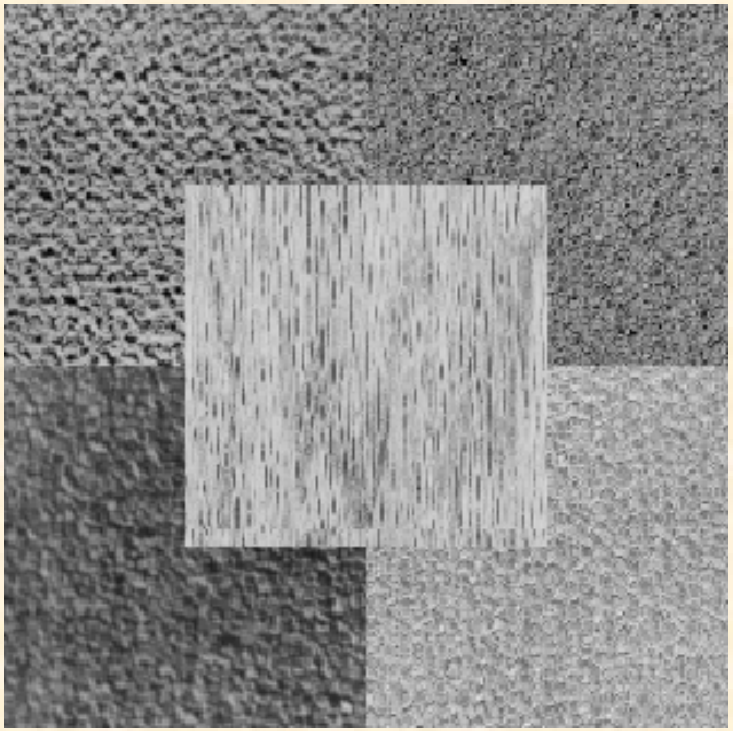
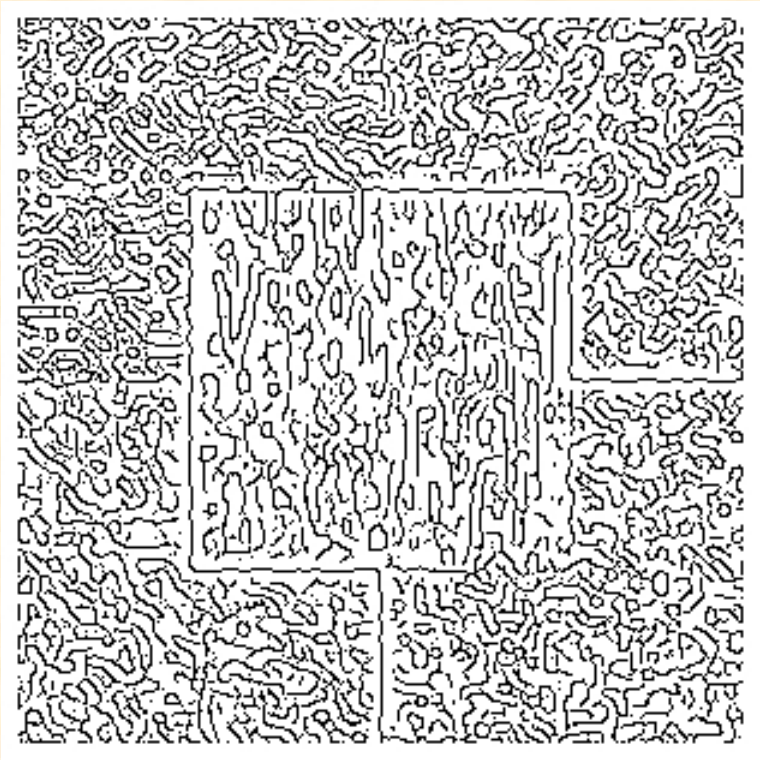
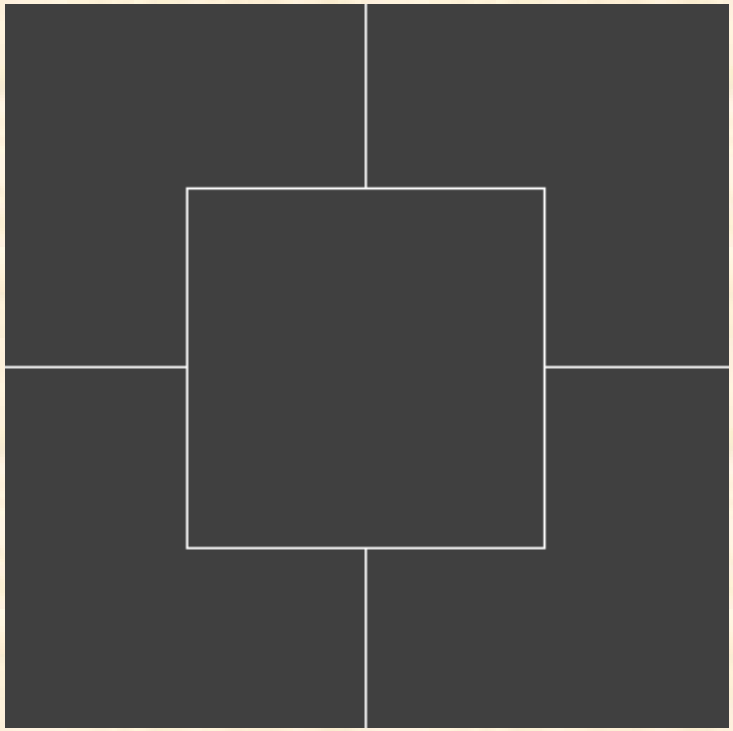
Texture Image





Output of Canny's algorithm

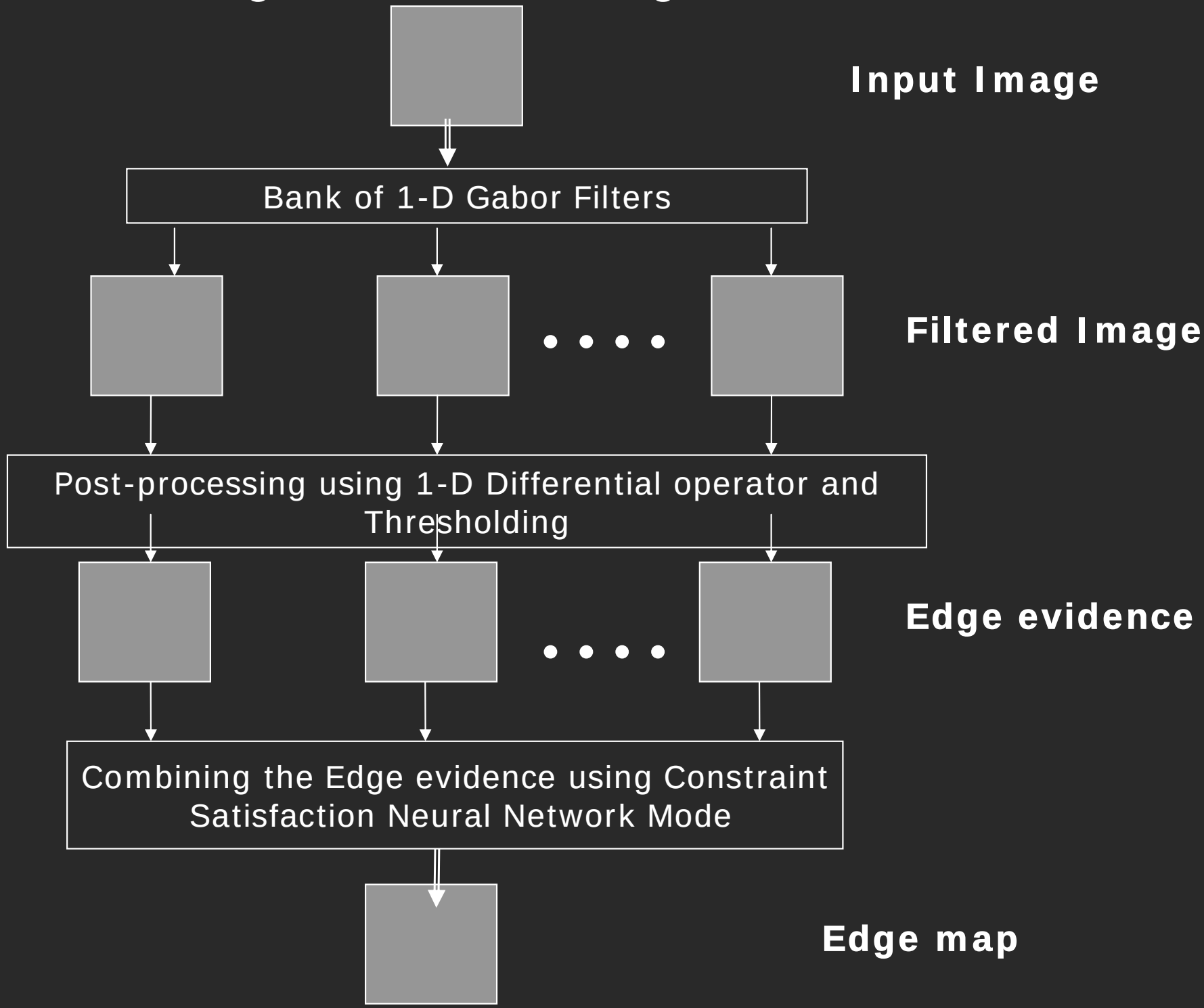


Desired output

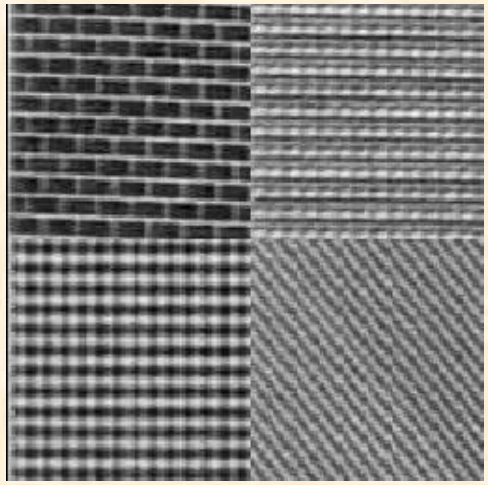
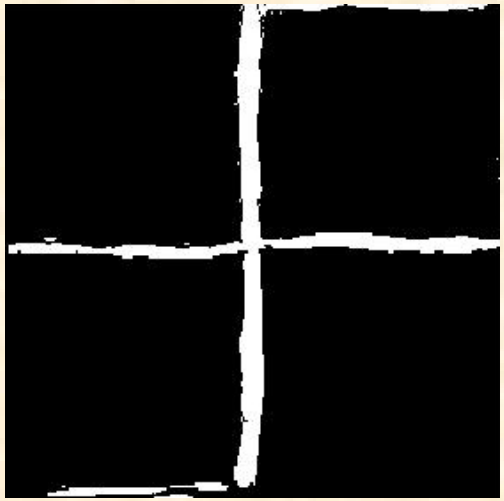
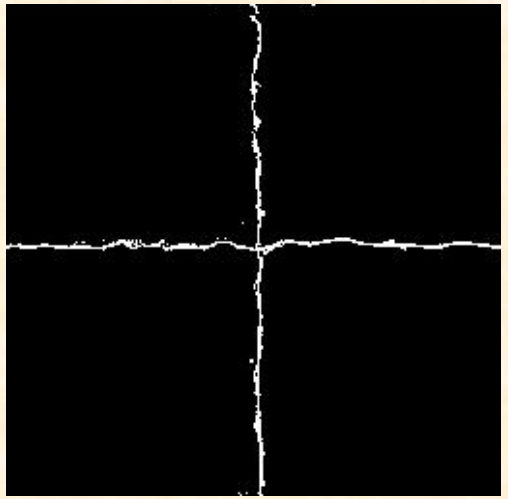
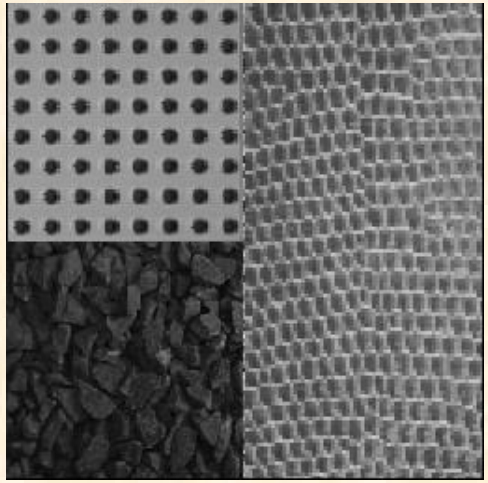
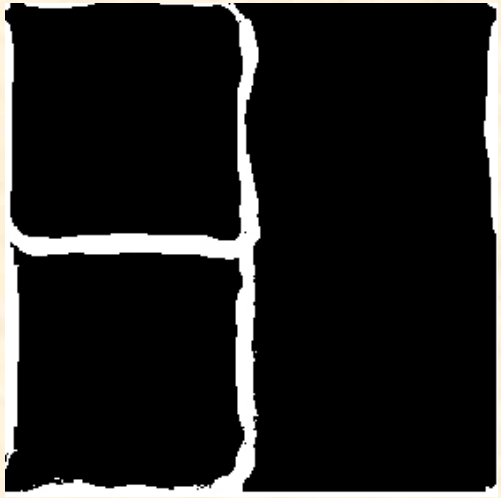
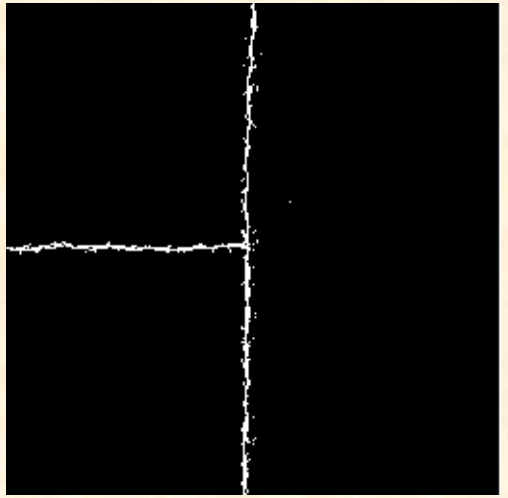
Texture Boundary Detection

- Edge extraction using 2-D Gabor filters smears the edge information
- The magnitude of the 1-D Gabor filter output is used as a feature to detect boundaries for texture-like images
- Advantage of 1-D processing: Feature extraction and edge extraction are applied along orthogonal directions. The Gaussian function (1-D) of the Gabor filter will not effect the edge information in the orthogonal direction
- The edge evidence obtained from a set of Gabor filters are combined using a constraint satisfaction neural network to obtain the final output

Texture Edge Extraction using a set of 1-D Gabor Filters



Results of Edge Extraction using Gabor Magnitude (contd.)

Gray level Image	2-D Gabor Filter Bank	1-D Gabor Filter bank
		
		

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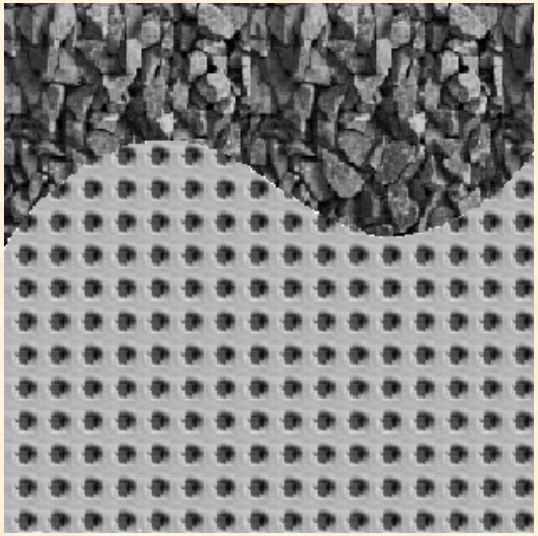
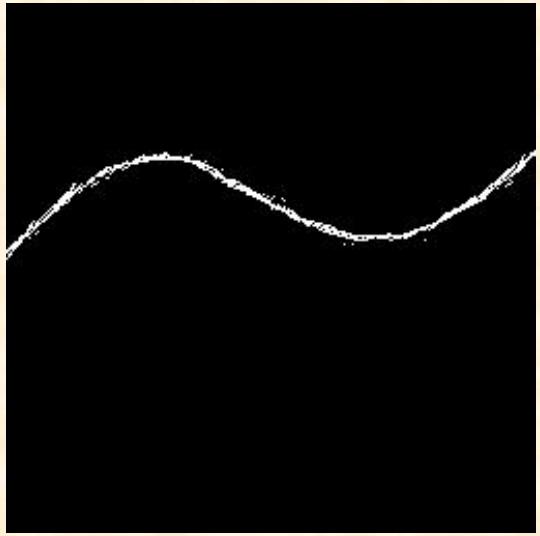
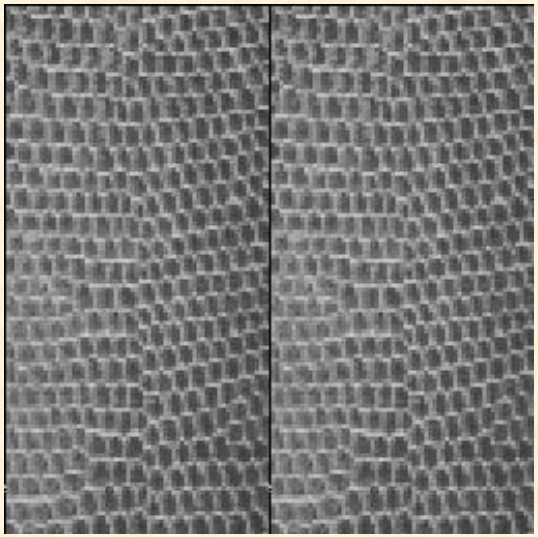
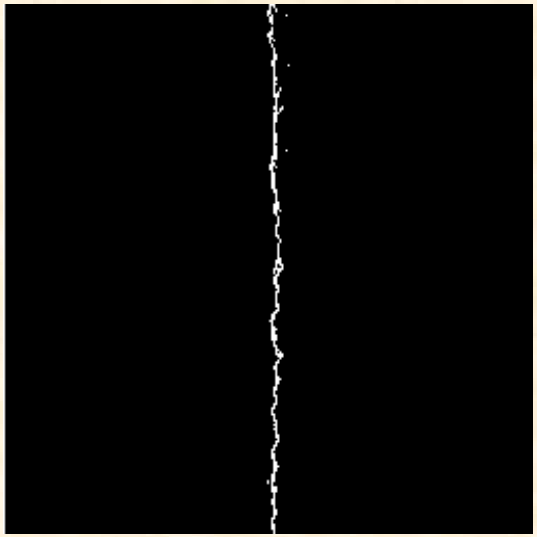
Results of Edge Extraction using Gabor Magnitude (contd.)

Gray level Image	2-D Gabor Filter Bank	1-D Gabor Filter bank
		
		

< Prev

Next >

- Filtering methods:
  - Discrete Wavelet Transform (DWT) (Daubechies 8-Taps)
  - Gabor Filter (Bank of 8 Gabor filters)
  - Discrete Cosine Transform (DCT) (9 filters) Ref: [Ng 92]
  - Gaussian Markov random field models Ref: [Cesmeli 2001]
  - Combination of DWT and Gabor filter Ref: [Rao 2004]
  - Combination of DWT and MRF Ref: [Wang 99]
- Non-linearity:
  - Magnitude (| . |)
- Smoothing:
  - Gaussian filter
- Feature vectors:
  - Mean (computed in a local window around a pixel)
- Classification:
  - Fuzzy-*C* Means (FCM) (unsupervised classifier)

• Combine Edge and region map using a CSNN

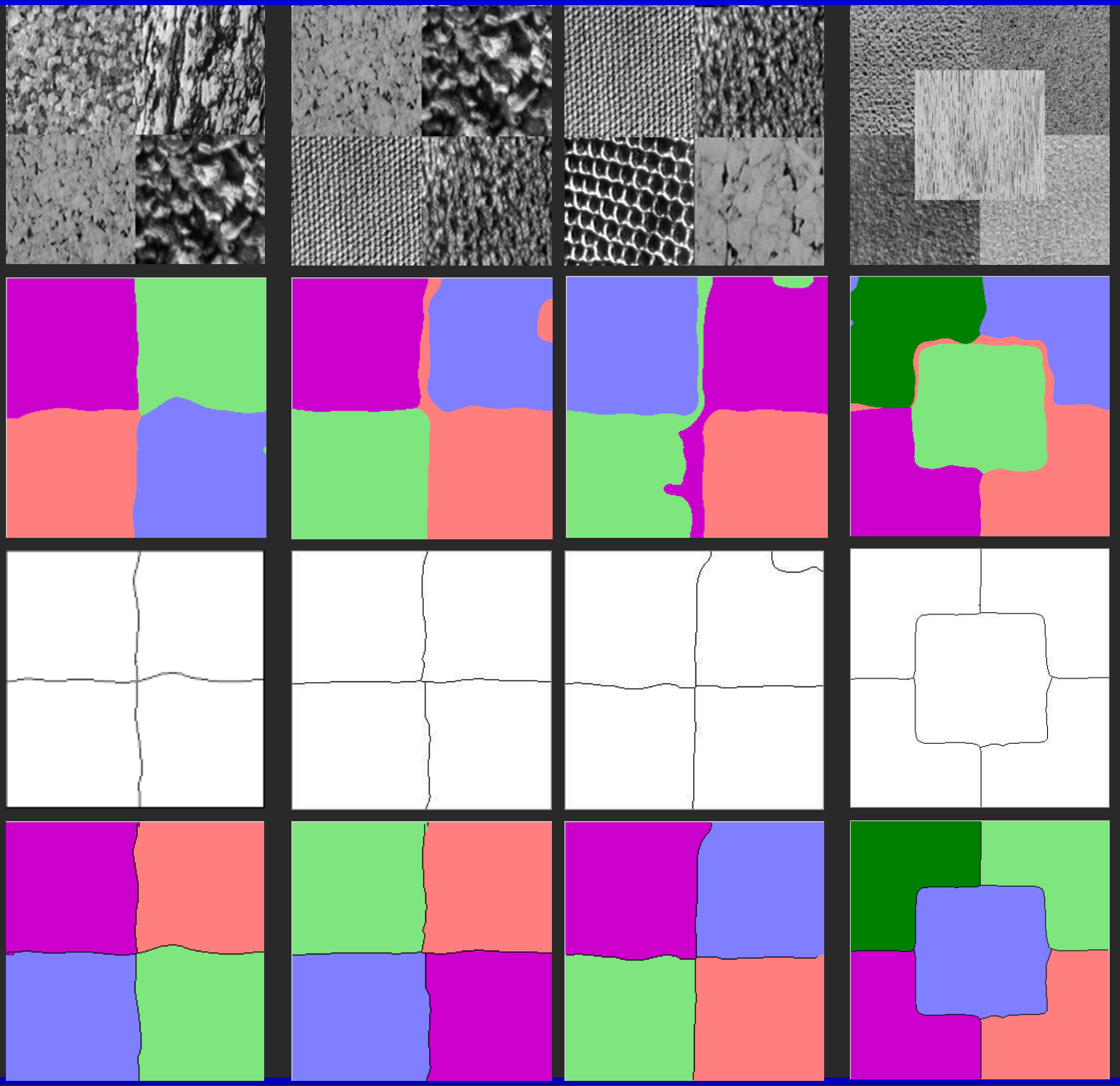
Results

Input Image

Segmented map before integration

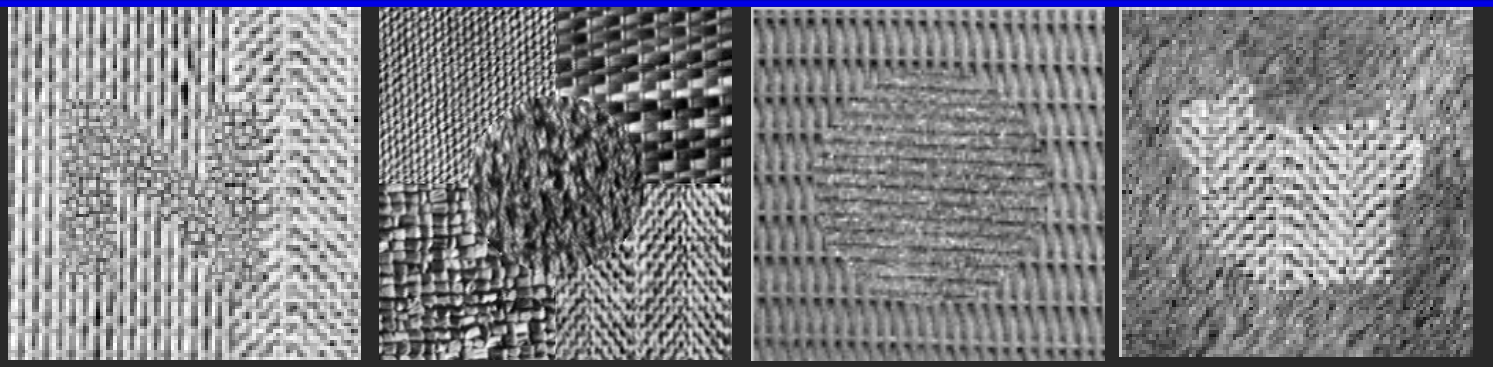
Edge map before integration

Segmented map and Edge map after integration

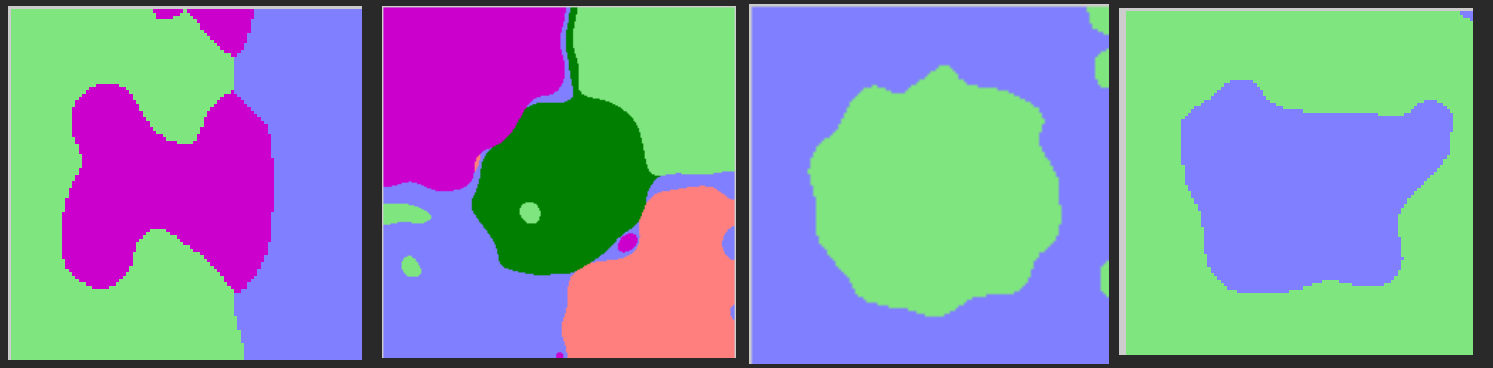


Results

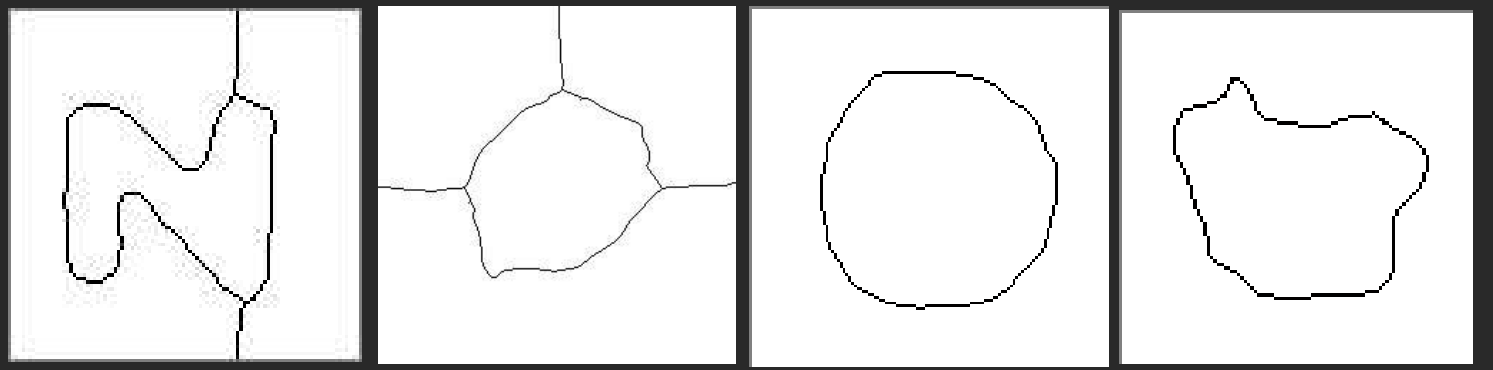
Input Image



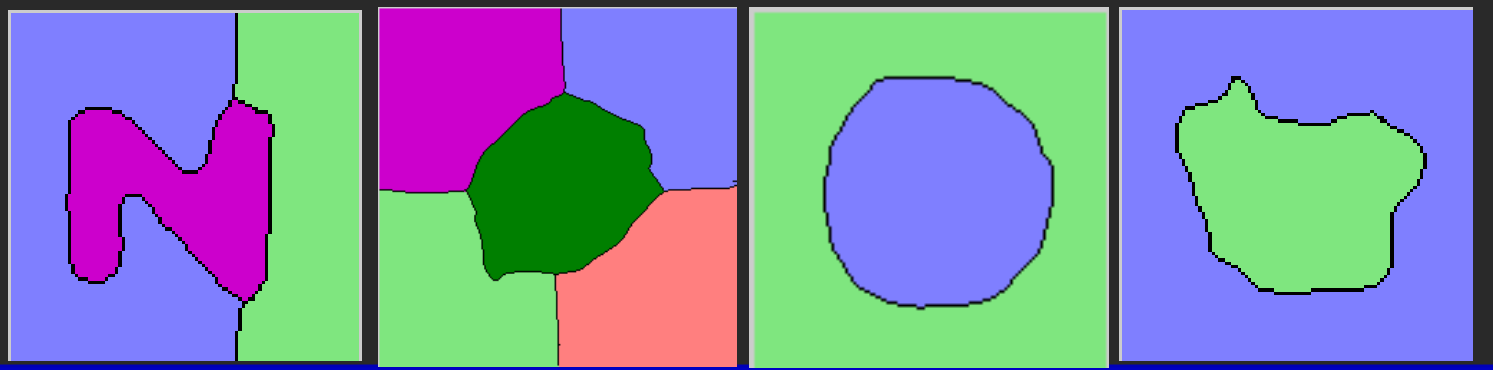
Segmented map before integration



Edge map before integration



Segmented map and Edge map after integration



GLCM based texture feature (statistical)

The **Grey Level Co-occurrence Matrix, GLCM**
(also called the **Grey Tone Spatial Dependency Matrix**)

The GLCM is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image.

The GLCM is usually defined for a series of "second order" texture calculations.

Second order means they consider the relationship between groups of two pixels in the original image.

First order texture measures are statistics calculated from the original image values, like variance, and do not consider pixel relationships. Third and higher order textures (considering the relationships among three or more pixels) are theoretically possible but not implemented due to calculation time and interpretation difficulty.

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

A small image neighborhood

Spatial relationship between two pixels:

NPV> / RPV	0	1	2	3
0				
1				
2				
3				

Neighbor/Reference Pixel Value

GLCM texture considers the relation between two pixels at a time, called the reference and the neighbour pixel. Let, the neighbour pixel is chosen to be the one to the east (right) of each reference pixel. This can also be expressed as a (1,0) relation: *(i, j) -> (i+1, j).*

Each pixel within the window becomes the reference pixel in turn, starting in the upper left corner and proceeding to the lower right.

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

A small image neighborhood

(-1,0) relation: *(i, j) -> (i-1, j).*

EAST GLCM

NPV> / RPV	0	1	2	3
0	2	2	1	0
1	0	2	0	0
2	0	0	3	1
3	0	0	0	1

WEST GLCM (why transpose ?)

NPV> / RPV	0	1	2	3
0	2	0	0	0
1	2	2	0	0
2	1	0	3	0
3	0	0	1	1

Symmetrical (1,0) GLCM

NPV> / RPV	0	1	2	3
0	4	2	1	0
1	2	4	0	0
2	1	0	6	1
3	0	0	1	2

Expressing the GLCM as a probability:

This is the number of times this outcome occurs, divided by the total number of possible outcomes.

This process is called normalizing the matrix. Normalization involves dividing by the sum of values.

Symmetrical (1,0) GLCM

NPV> / RPV	0	1	2	3
0	4	2	1	0
1	2	4	0	0
2	1	0	6	1
3	0	0	1	2

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

.166 (4/24)	.083 (2/24)	.042 (1/24)	0 (0/24)
.083	.166	0	0
.042	0	.25	.042
0	0	.042	.083

A small image neighborhood

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

Find,
(1,0), South GLCM (solve it):

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

Normalized symmetrical vertical GLCM

.250	0	.083	0
0	.166	.083	0
.083	.083	.083	.083
0	0	.083	0

Any reason for Diagonal dominance ?

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5. B. Thai and G. Healey, Optimal Spatial Filter Selection for Illumination-Invariant Color Texture Discrimination, IEEE Trans. Systems, Man and Cybernetics, Part B: Cybernetics, Vol. 30, No. 4, August 2000, pp 610-615.
6. J. Randen and J. S. Husoy, "Optimal Filter-bank Design for Multiple texture Discrimination", Proceedings of the International Conference on Image Processing (ICIP '97), pp 215-218.
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