Basic Image Processing

PPKE-ITK

Lecture 5.

Texture analysis

Motivation: find the object!

Solution: color filtering

Solution: texture segmentation

Textures - definition

- Textures demonstrate the difference between an artificial world of objects whose surfaces are only characterized by their color and reflectivity properties to that of real world imagery
- How we can define texture: microstructure
  - certainly not: an arbitrary pattern that extends over a large image
- Basic properties
  - Small elementary pattern which is repeated periodically or quasi-periodically in space (like pattern on a wall paper)
- It is sufficient to describe:
  - Small elementary pattern
  - Repetition rules (characteristic scales)
- Types
  - Artificial (Julesz, Pratt, Gagalowic)
  - Natural (Brodatz)

Textures - definition

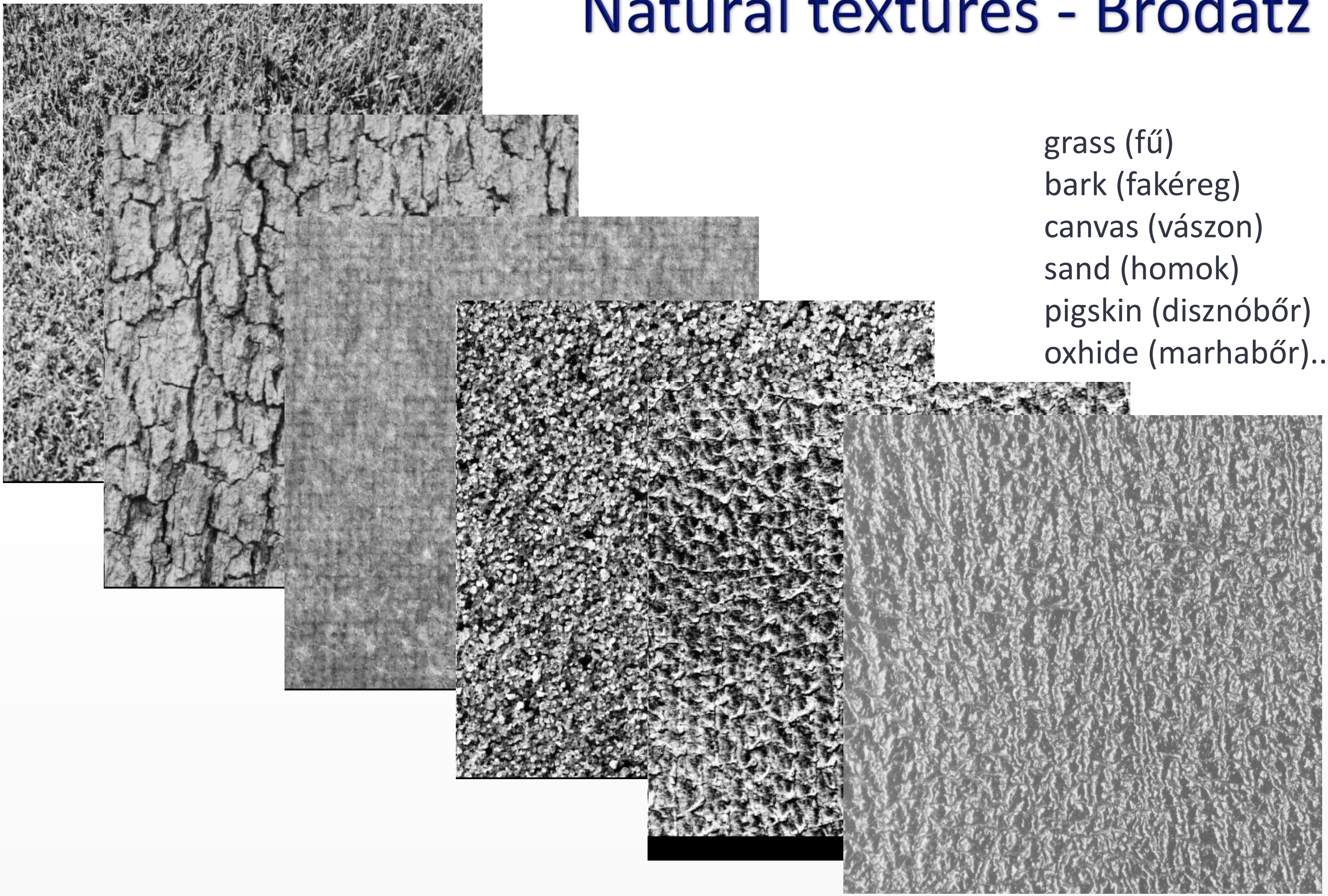
- Hawkins:
  - Some local ‚order' is repeated over a region which is large in comparison to the order's size,
  - The order consists in the nonrandom arrangement of elementary parts
  - The parts are roughly uniform entities having approximately the same dimensions everywhere within the textured region
- Description:
  - *coarseness* ~ period of repetition
    - e.g. wool is "coarser" than silk, under the same conditions
  - fineness / rudeness, contrast, orientation, arrangement ...

Texture



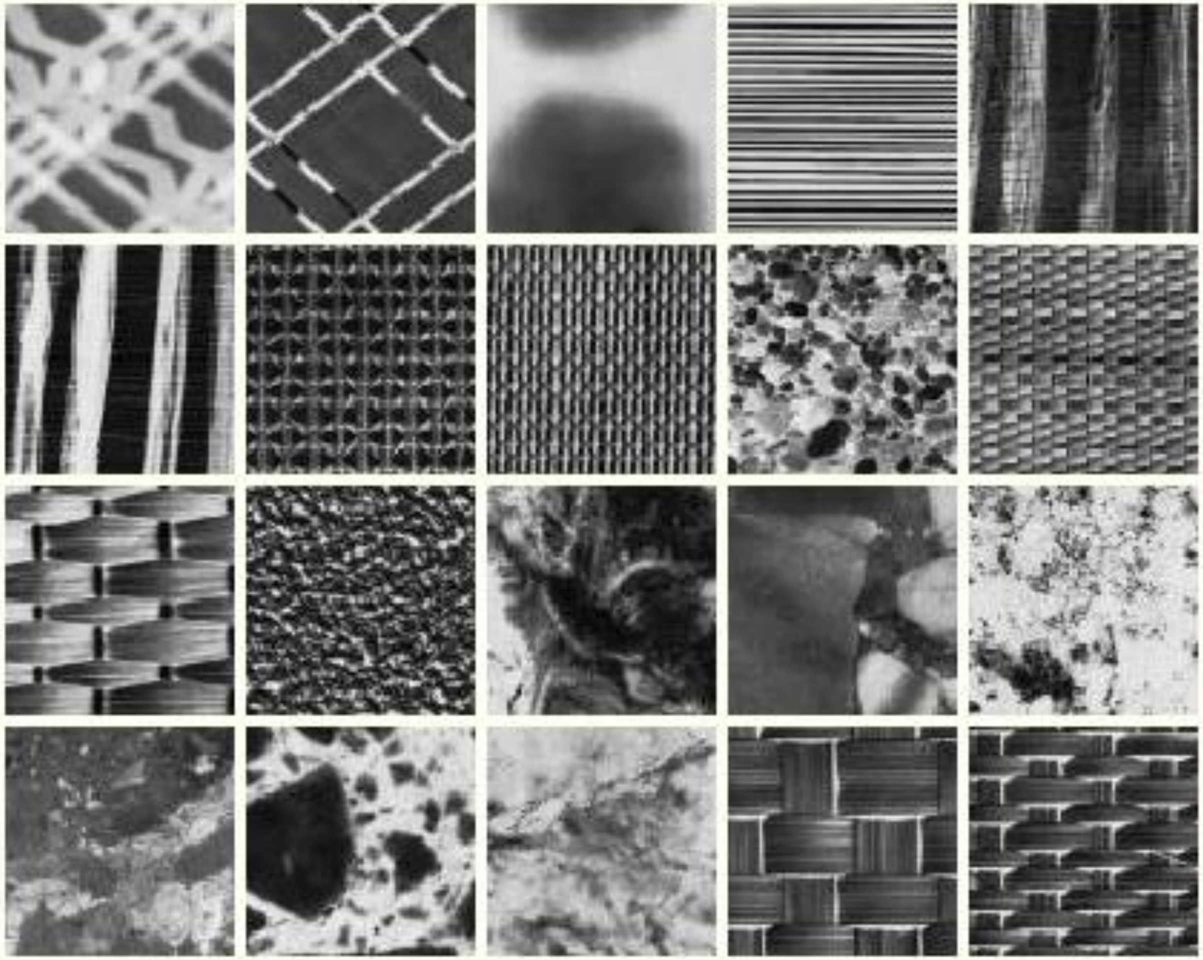
- A texture is an image that follows some statistical properties
- It has similar structures repeated over and over again

Natural textures - Brodatz

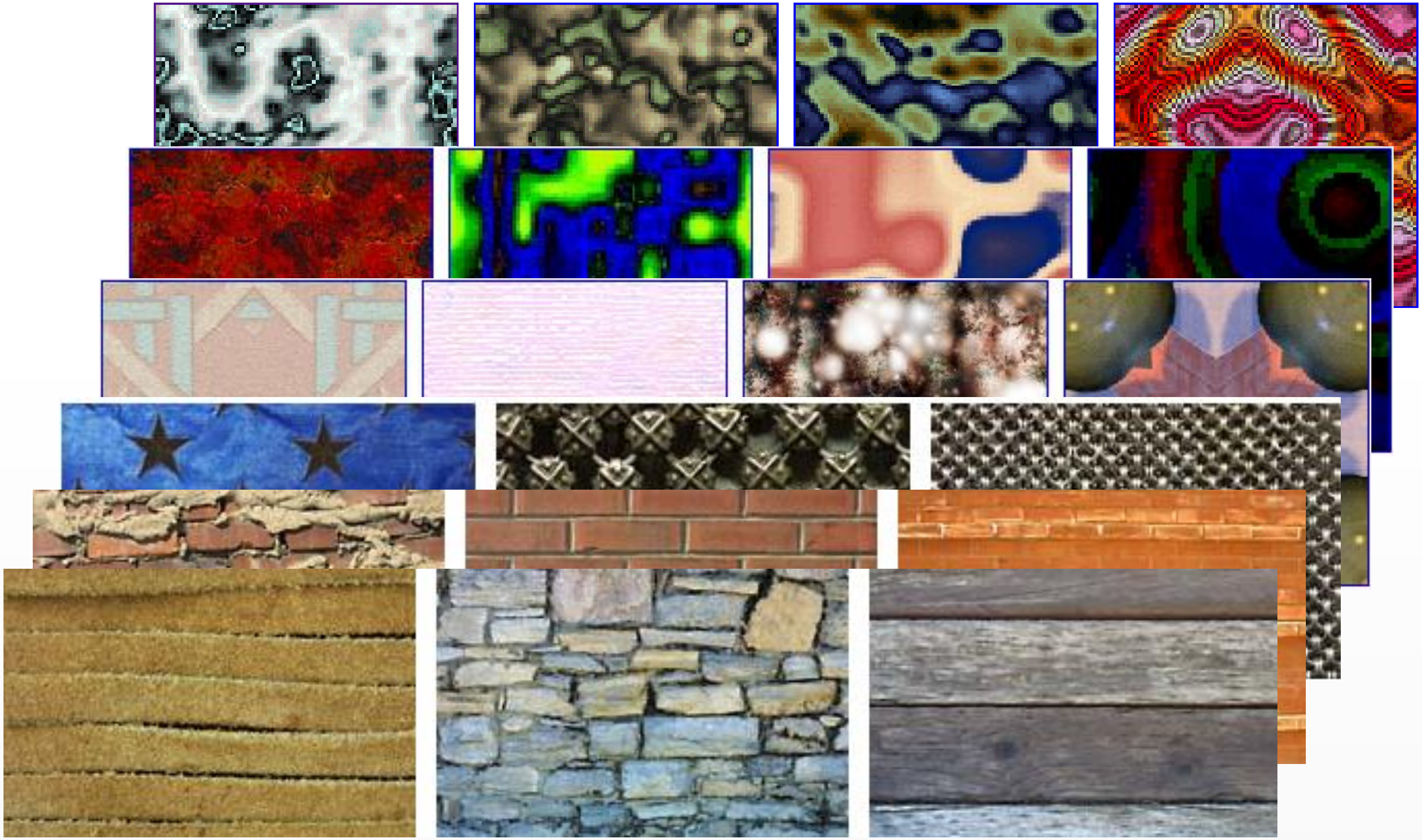


grass (fű)
bark (fakéreg)
canvas (vászon)
sand (homok)
pigskin (disznóbőr)
oxhide (marhabőr)...

Further natural textures from Brodatz



Artificial textures

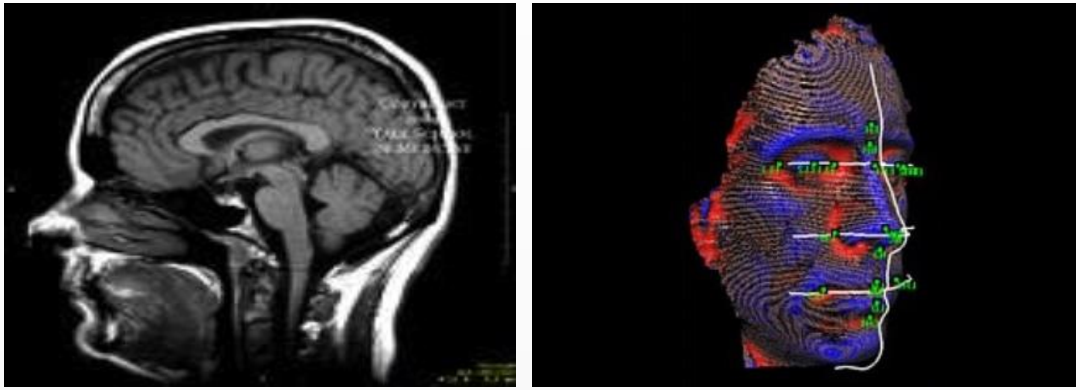


Application Areas of Texture Analysis

Food processing industry

Biometrics analysis (fingerprint, iris or retina, etc.)

Medical image analysis



Global information system (GIS) (for land, etc. analysis)

Texture analysis:

- There are various primary issues in texture analysis:
  - *TEXTURE CLASSIFICATION*
  - *TEXTURE SEGMENTATION*
  - *SHAPE RECOVERY FROM TEXTURE, and*
  - *MODELING*.

Texture classification

- In texture **classification**, the problem is **identifying** the given textured region from a given set of texture classes.
  - The texture analysis algorithms **extract distinguishing feature** from each region to facilitate classification of such patterns.

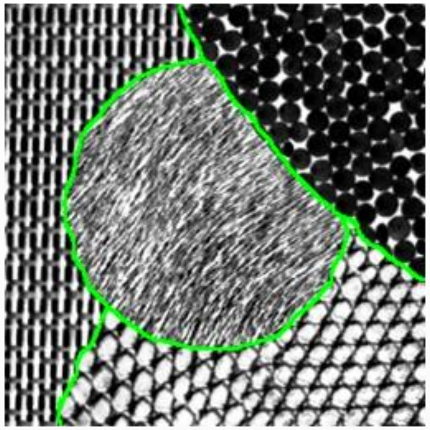
Texture classification

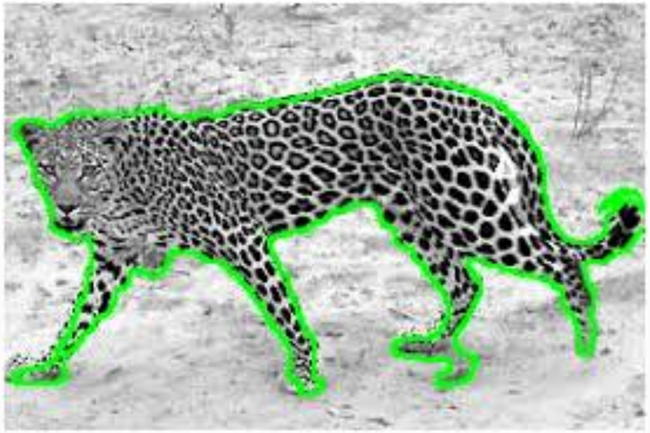
- In texture **classification**, the problem is **identifying** the given textured region from a given set of texture classes.
  - The texture analysis algorithms **extract distinguishing feature** from each region to facilitate classification of such patterns.

Novel image to be classified

Texture segmentation

- Unlike texture classification, texture **segmentation** is concerned with automatically determining the **boundaries** between various textured regions in an image.
- Both reign-based methods and boundary-based methods have been attempted to segments texture images.



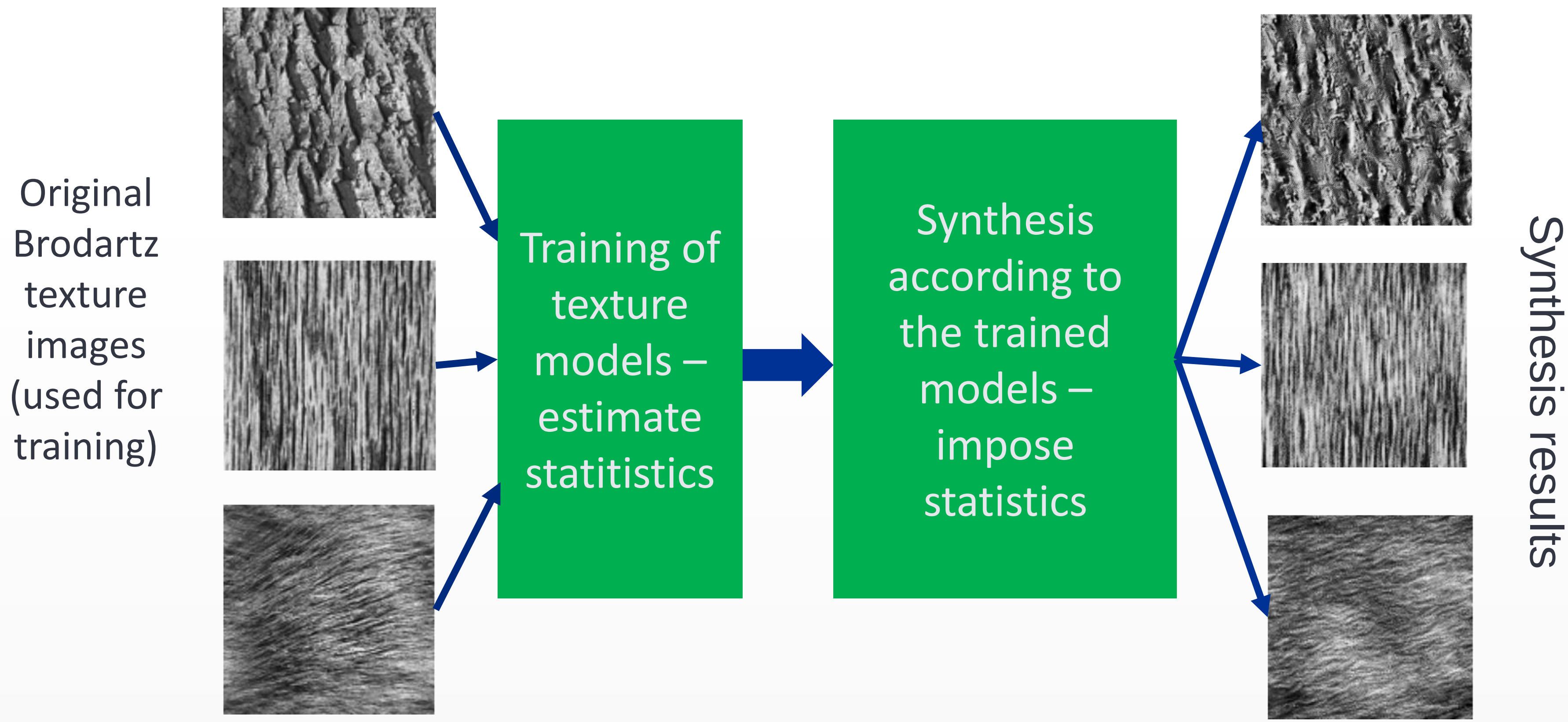


Shape recovery from texture

- Image plane variation in the texture properties, such as density, size and orientation of texture primitives, are the cues exploited by shape –from-texture algorithms.
- Quantifying the changes in the shape of texture elements is also useful to determine surface orientation.

Texture modeling

- Specify a model that clearly identifies the given pattern sample



Techniques for Texture Extraction

- There are various techniques for texture extraction. Texture feature extraction algorithms can be grouped as follows:
  - **Statistical**
  - **Geometrical**
  - **Model based**
  - **Signal Processing**

Statistical methods

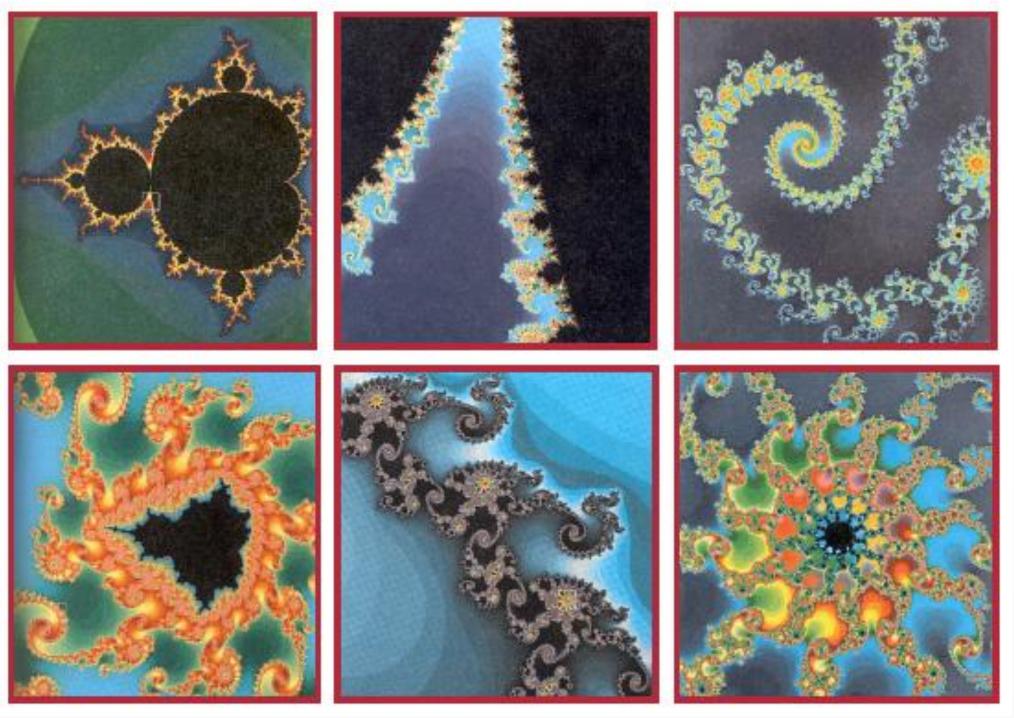
1. Local features
    - Grey level of central pixels,
    - Average of grey levels in window,
    - Median,
    - Standard deviation of grey levels,
    - Difference of maximum and minimum grey levels,
    - Difference between average grey level in small and large windows,
    - Kirsch feature,
    - Combine features
2. Galloway
    - run length matrix
3. Haralick
    - co-occurrence matrix

Geometrical methods

- Steps
  1. **Threshold** images into binary images of *n* grey levels.
  2. Calculate **statistical** features of **connected areas**.

Model based methods

- These involve building mathematical models to describe textures:
  - **<u>Markov random fields</u>** (see: later – image segmentation lecture)
  - Fractals:

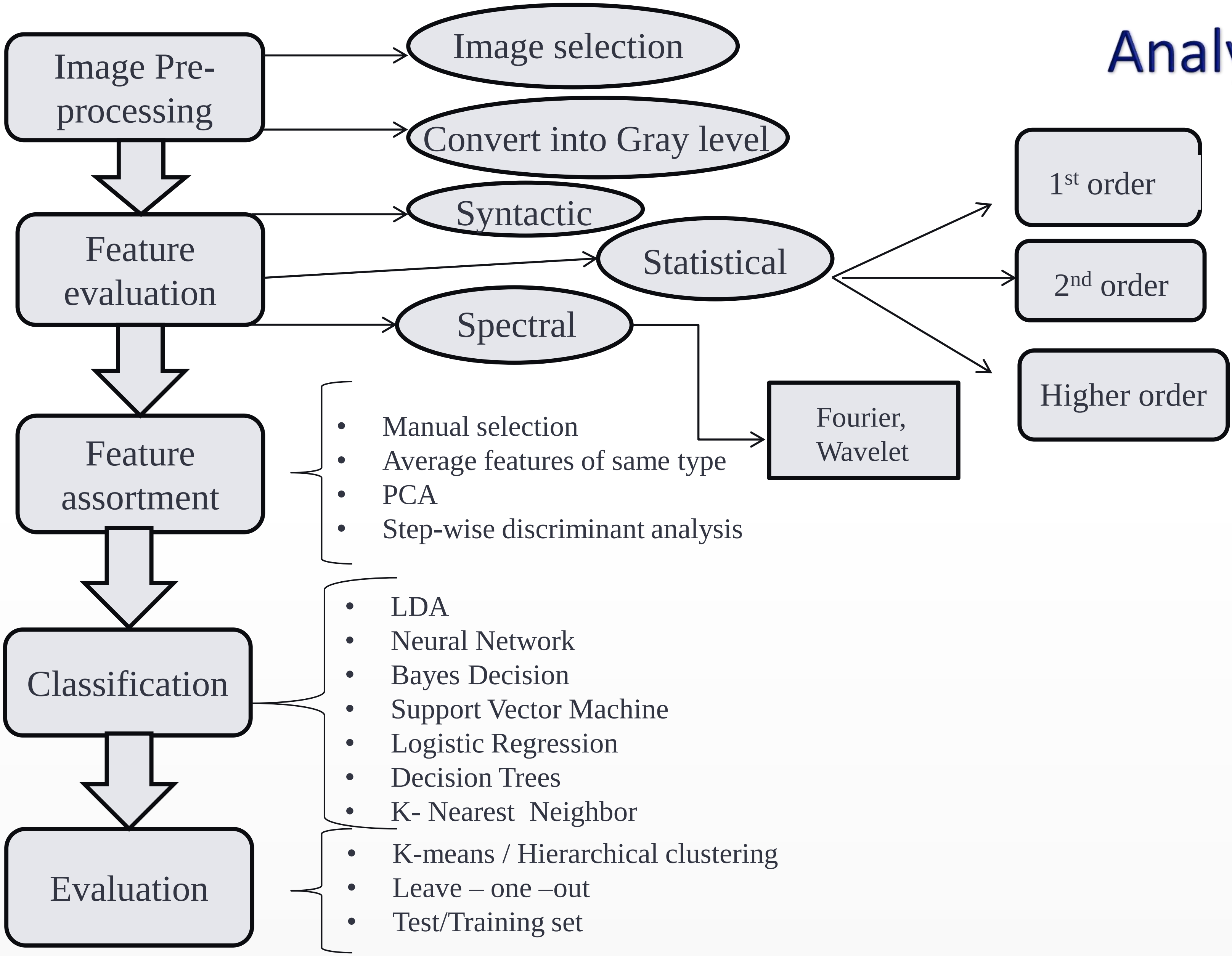


Signal processing includes

- These methods involve transforming original images using filters and calculating the energy of the transformed images.

- **Law’s masks (see: today – later)**
- Laines – Daubechies wavelets
- **Fourier transform (see: last lecture)**
- **Gabor filters (see: today – later)**

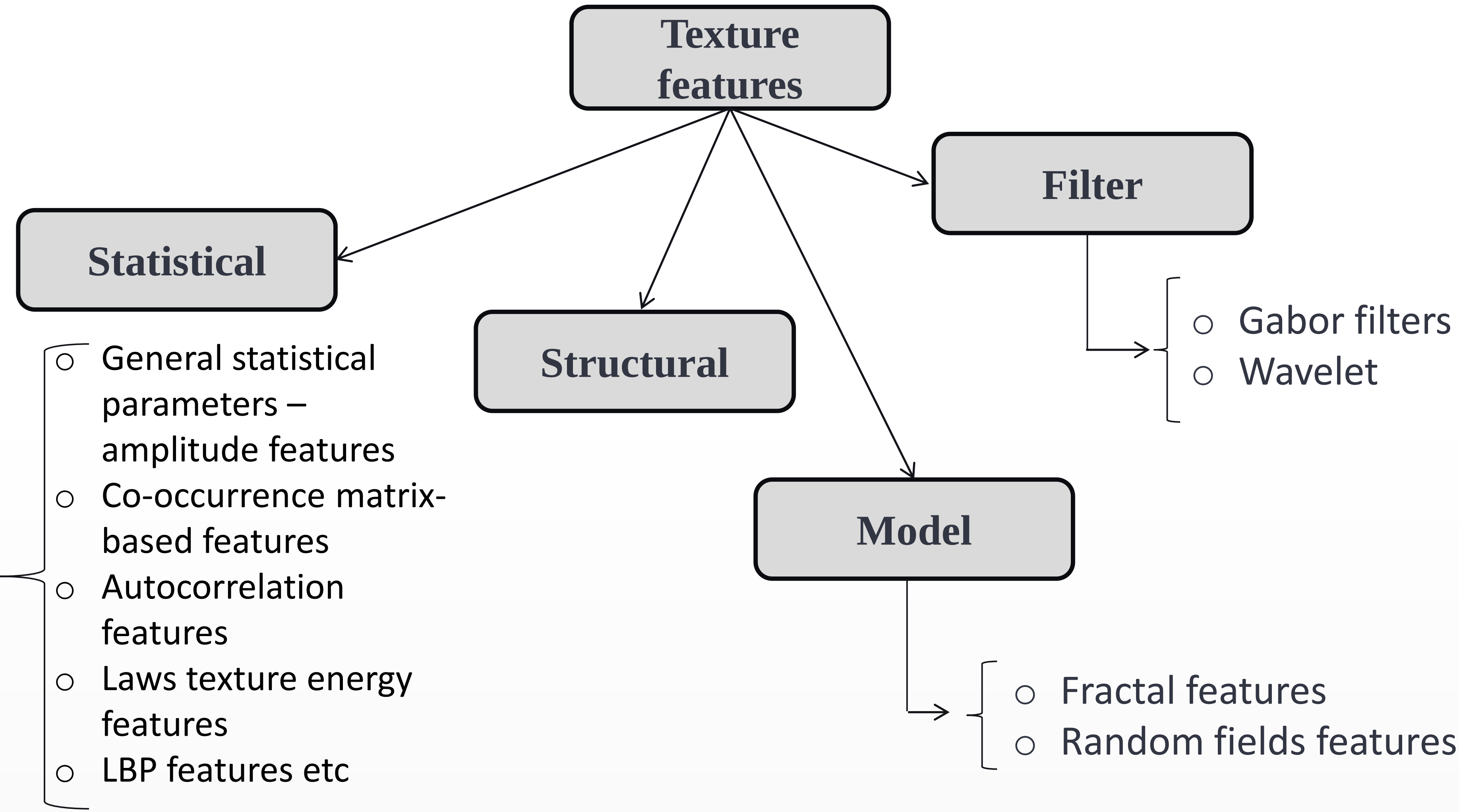
Flowchart for Texture Analysis



Discrimination vs. classification of textures

- Discrimination
  - Classification - grouping of blobs or points, and classifying them into various classes (local attributes)
  - Segmentation - separation of spots / areas (local properties + neighborhoods)
- Classification
  - Supervised approach
    - take samples of textures (statistics, metrics) then
    - examine the similarity of new textures
  - Unsupervised
    - evaluate statistics
    - sample categorization into classes

Methods for Texture Features



Statistical features
Amplitude features

- Amplitude-features
  - Mean

$$M(j,k)=\frac{1}{(2w+1)^2}\sum_{m=-w}^{w}\sum_{n=-w}^{w}F(j+m,k+n)$$

  - Deviation

$$S(j,k)=\frac{1}{(2w+1)^2}\left[\sum_{m=-w}^{w}\sum_{n=-w}^{w}\left[F(j+m,k+n)-M(j+m,k+n)\right]^2\right]^{1/2}$$

Statistical features
Gray Level Co-occurrence Matrix (GLCM)

- Also referred as **co-occurrence distribution**.
- It is the most classical second-order statistical method for texture analysis.
- An image is composed of **pixels** each with an intensity (a specific gray level), the GLCM is a tabulation of how often different combinations of gray levels co-occur in an image or image section.
- **Gray Level Co-occurrence Matrix** (GLCM) filters operate by computing, for each filter window position, how often specific pairs of image cell values occur in neighboring cell positions (such as one cell to the right).
- The results are tabulated in a co-occurrence matrix, and specific statistical measures are computed from this matrix to produce the filtered value for the target cell

Statistical features
First vs. second order statistics examples

- First order statistics example: simple histogram
  - Measures the number of different gray value occurrences of independent pixels
  - h_i: number of pixels in the image with gray value i
- Second order statistics example: GLCM
  - Measures the frequencies of joint gray value occurrences of different pixel pairs with a pre-defined spatial offset
  - $p_{ij}(\Delta x, \Delta y)$: frequency of pixel pairs with an offset $(\Delta x, \Delta y)$, where the gray value of the first pixel is i and the gray value of the second pixel is j
  - For example: Δx=1, $\Delta y = 0$, i=0, j=255: frequency of one-pixel-wide vertical black-white transitions in an image

Statistical:
Co-occurrence Matrix-based Features

- It is a matrix of *frequencies* at which → two pixels, separated by a certain vector, occur in the image.
- Co-occurrence matrix is defined as,

$$p_{ij}(\Delta x, \Delta y) = W \cdot Q(i, j | \Delta x, \Delta y)$$

where,

$$W = \frac{1}{(M - \Delta x)(N - \Delta y)} \qquad Q(i, j | \Delta x, \Delta y) = \sum_{n=1}^{N-\Delta y} \sum_{m=1}^{M-\Delta x} A$$

where,

$$A = \begin{cases} 1 & \text{if } \ f(m,n) = i \text{ and } f(m+\Delta x, n+\Delta y) = j \\ 0 & \text{otherwise} \end{cases}$$

Computation of Co-occurrence Matrix

- It has size $N \times N$ (N = Number of gray-values) i.e., the rows & columns represent the set of possible pixel values.
- Polar representation of the offset:
  - two parameters d, θ (instead of $\Delta x, \Delta y$):

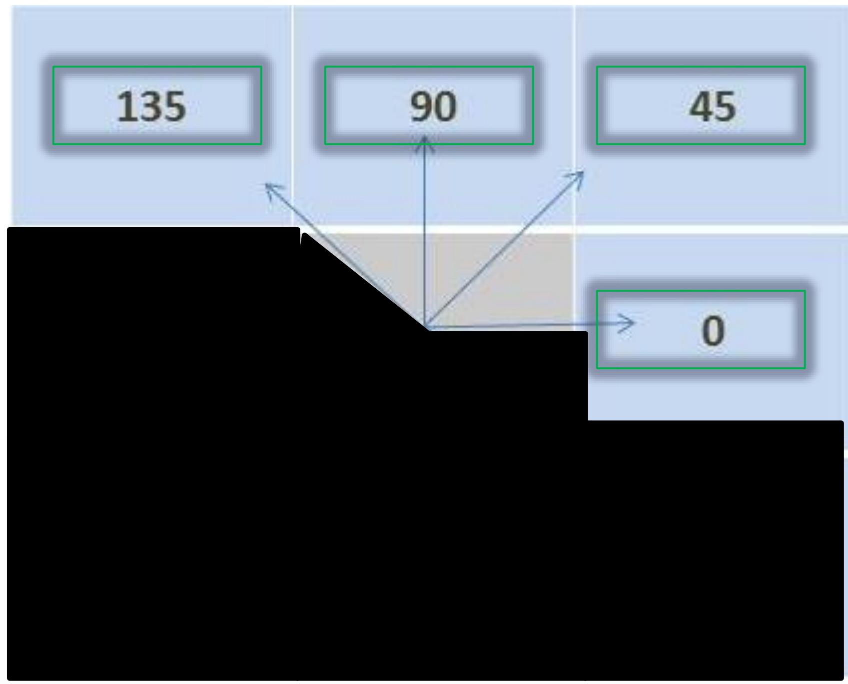
d → Relative **distance** between the pixel pair

(measured in pixel number. e.g., 1, 2, …)

θ → Relative **orientation** / rotational angle.

(e.g., 0º, 45º, 90º, 135º, …)

8 Directions/orientations (θ) of Adjacency



we consider θ as horizontal (0°), front diagonal (45°), vertical (90°) and back diagonal (135°)

Computation of Co-occurrence Matrix

Find the **number of co-occurrences** of pixel *i* to the neighboring pixel value *j*

Image matrix

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

Pixel values: 0,1,2,3. **Thus,** $N = 4$

Thus, *size* of CM = 4x4

$d = 1$

θ = horizontal (0°)

i/j	0	1	2	3
0	#(0,0)	#(0,1)	#(0,2)	#(0,3)
1	#(1,0)	#(1,1)	#(1,2)	#(1,3)
2	#(2,0)	#(2,1)	#(2,2)	#(2,3)
3	#(3,0)	#(3,1)	#(3,2)	#(3,3)

Example: Computation (contd.)

i/j	0
0	#(0,0)

$d = 1$

θ = horizontal (0°)

0 →	0	1	1
0 →	0	1	1
0	2	2	2
2	2	3	3

→

2			

Example: Computation (contd.)

$d = 1$ θ = horizontal (0°)

Image

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

2	2	1	0

CM for the Image

i/j	**0**	**1**	**2**	**3**
0		**#(0,1)**	**#(0,2)**	**#(0,3)**
1				
2				
3				

Example: Computation (contd.)

$d = 1$ $\theta =$ **horizontal** $(0°)$

Image

0	0	1	1
0	0	1	1
0	2	2	2
2	2	3 →	3

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

CM for the Image

i/j	0	1	2	3
0	#(0,0)	#(0,1)	#(0,2)	#(0,3)
1	#(1,0)	#(1,1)	#(1,2)	#(1,3)
2	#(2,0)	#(2,1)	#(2,2)	#(2,3)
3	#(3,0)	#(3,1)	#(3,2)	#(3,3)

Example: Computation (contd.)

$d = 1$ $\theta = \textbf{vertical}(90°)$

Image

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

→

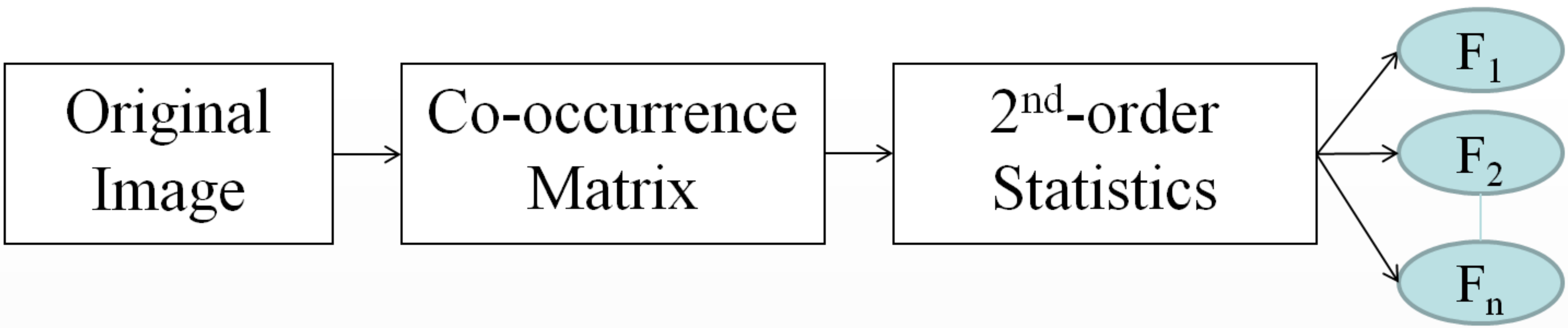
3	0	2	0
0	2	2	0
0	0	1	2
0	0	0	0

CM for the Image

i/j	**0**	**1**	**2**	**3**
0	**#(0,0)**	**#(0,1)**	**#(0,2)**	**#(0,3)**
1	**#(1,0)**	**#(1,1)**	**#(1,2)**	**#(1,3)**
2	**#(2,0)**	**#(2,1)**	**#(2,2)**	**#(2,3)**
3	**#(3,0)**	**#(3,1)**	**#(3,2)**	**#(3,3)**

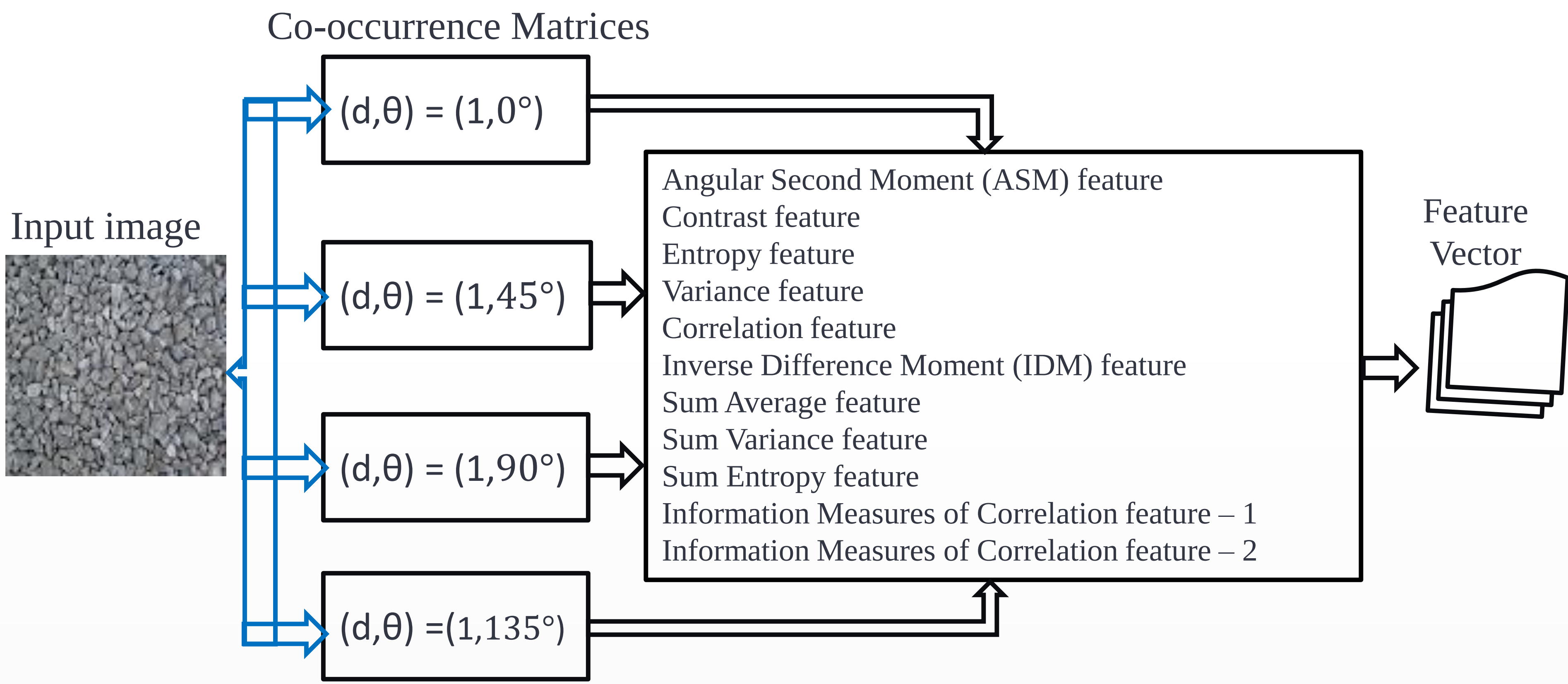
Features on co-occurrence matrix

- Co-occurrence matrices capture properties of a texture
- But they are *not directly useful* for further analysis
  (e.g., comparison of two textures)



11 Numeric features are computed from a matrix

Features on co-occurrence matrix



Energy

- Also called **Uniformity or Angular second moment**.
- **Measures the textural uniformity that is pixel pair repetitions.**
- Detects disorders in textures.
- Energy reaches a maximum value equal to one

$$Energy=\sum_i \sum_j p_{ij}^2$$

Entropy

- **Measures the disorder or complexity of an image.**
- The entropy is large when the image is not texturally uniform.
- Complex textures tend to have high entropy.
- Entropy is strongly, but inversely correlated to energy.

$$Entropy = -\sum_i \sum_j p_{ij} \log_2 p_{ij}$$

Contrast

- **Measures the spatial frequency of an image and is difference moment of GLCM**.
- It is the difference between the highest and the lowest values of a contiguous set of pixels.
- It measures the amount of local variations present in the image.

$$Contrast=\sum_i \sum_j (i-j)^2 p_{ij}$$

Homogeneity

- Also called as **Inverse Difference Moment**.
- **Measures image homogeneity as it assumes larger values for smaller gray tone differences in pair elements**.
- It is more sensitive to the presence of near diagonal elements in the GLCM.
- It has maximum value when all elements in the image are same.
- Homogeneity decreases **if** contrast increases while energy is kept constant.
- Homogeneity(hom) = $\sum_i \sum_j \frac{1}{1+(i-j)^2} p_{ij}$

Variance

- **This statistic is a measure of heterogeneity and is strongly correlated to first order statistical variable such as standard deviation.**
- Variance increases when the gray level values differ from their mean

Variance(var)= $\sum_i \sum_j (i-\mu)^2 \, p_{ij}$

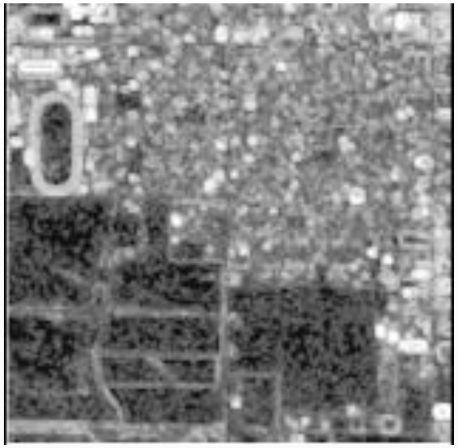
where μ is the mean of p_{ij}

GLCM Filters

- **Contrast** (Sum of Squares Variance)
  - measures gray-level contrast by using GLCM weighting factors equal to the square of the gray level difference. Thus the averaging weights are 0 for matrix position on the main diagonal and increase exponentially away from the diagonal. The filter result is 0 for areas with identical image values and is high where there are large differences in tone.

Input image

Thresholded Contrast



Contrast filter output

Features on co-occurrence matrix Examples

Feature	Comment
F2: Contrast	- Have discriminating ability. - Rotationally-variant.
F3: Entropy	- Have strong discriminating ability. - Almost rotational-invariant.
F4: Variance	- Have discriminating ability. - Rotational-invariant.
F5: Correlation	- Have strong discriminating ability. - Rotational-dependent feature.

Features on co-occurrence matrix

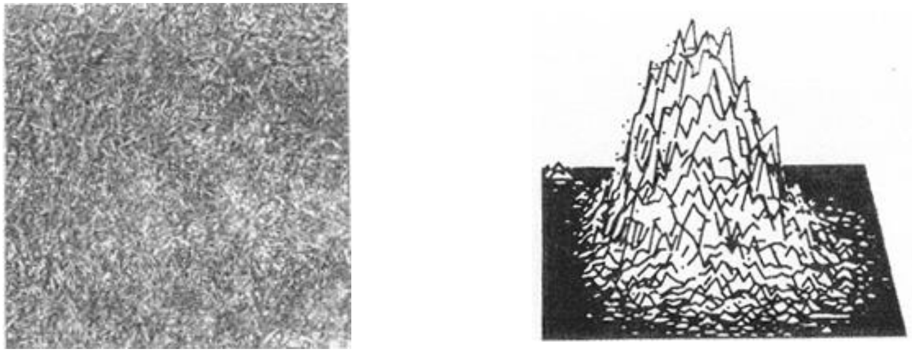
Feature	Comment
F7: Sum average	- Characteristics are similar to 'variance'/F4 - Rotational-invariant.
F10: Information Measure of Correlation–1	- It has almost similar pattern of 'sum average'/F7 but vary for various classes - Varies significantly with rotation
F11: Information Measure of Correlation–2	- It is computationally expensive compare to others. - Rotation-variant

Features on co-occurrence matrix

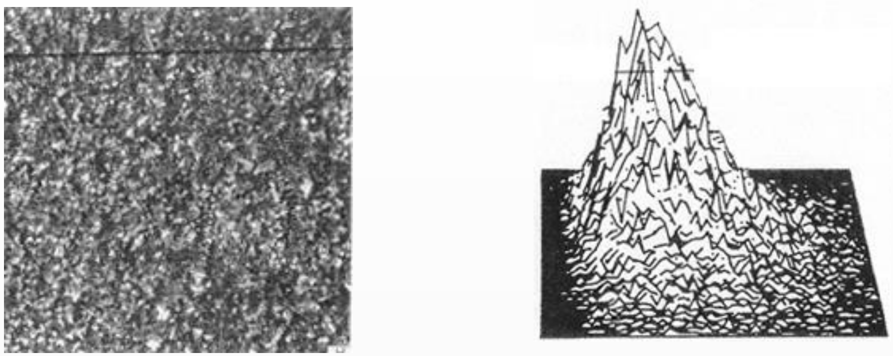
Feature	Comment
F1: Angular Second Moment / Energy	- No distinguishing ability
F6: Inverse Different Moment	- Similar to ‘angular second moment’/F1
F8: Sum Variance	- Similar to ‘variance’/F4
F9: Sum Entropy	- Similar to ‘entropy’/F3

Visualization of co-occurence histograms

- Dependency matrices
  - co-occurrence histograms
  - calculated in a given direction, and distance
  - smoother texture implies more steady response (less dependencies)
  - Coarse texture: dominant response along the main diagonal



Grass



Ivy (borostyán)

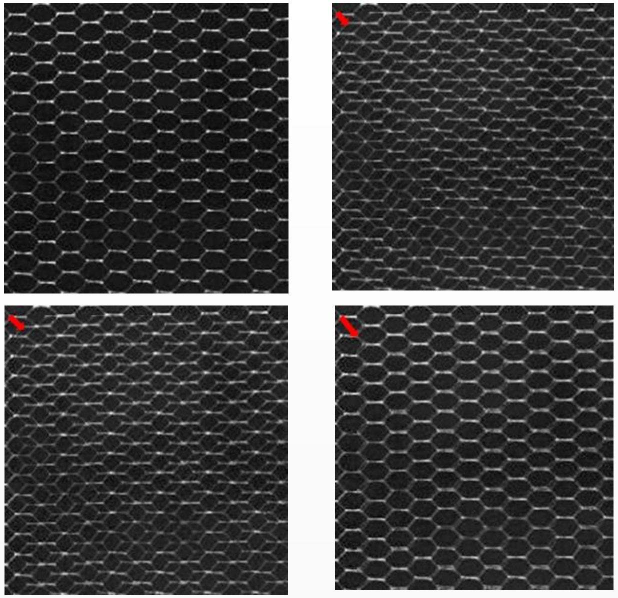
Grayscale dependency matrices for $r = 4, \theta = 0^{\circ}$

Statistical features
Autocorrelation function

- **Definition of autocorrelation:** compare the dot product (energy) of non shifted image with a shifted image

$$R_{II}(\Delta x, \Delta y) = \frac{\sum_{x=0}^{N} \sum_{y=0}^{N} I(x,y) I(x+\Delta x, y+\Delta y)}{\sum_{x=0}^{N} \sum_{y=0}^{N} I^2(x,y)}$$

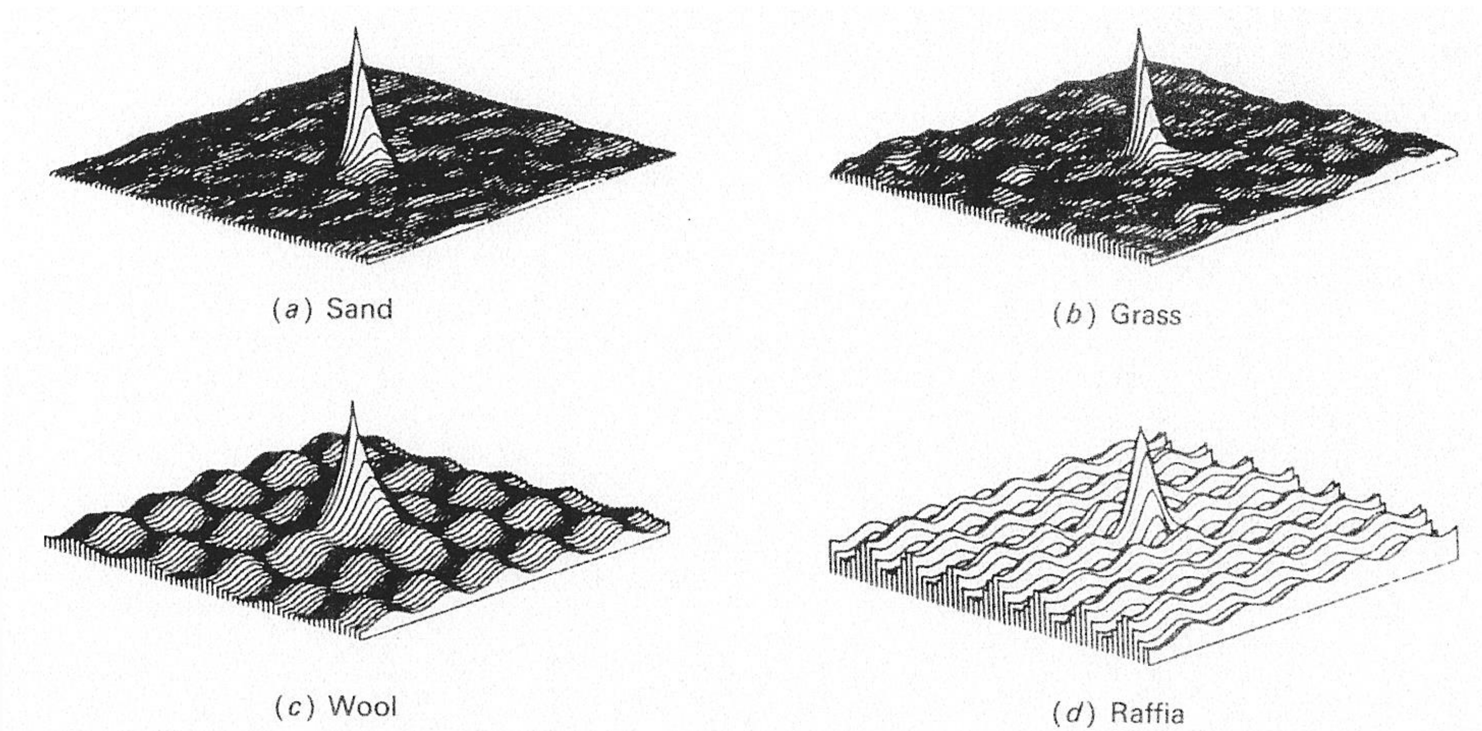
- Features:
  - Autocorrelation function can detect repetitive patterns of texels
  - Also defines fineness/coarseness of the texture



Different shift values

$\Delta x, \Delta y$

Textures – image features

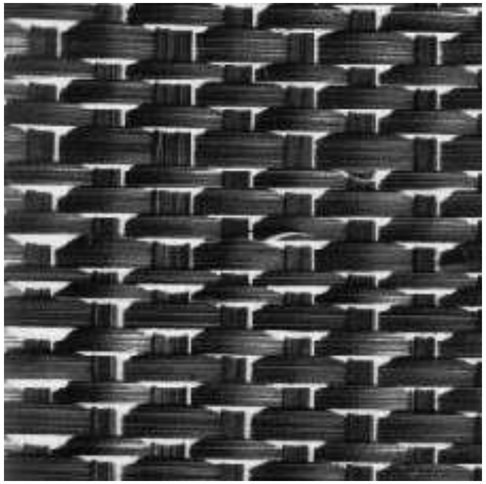
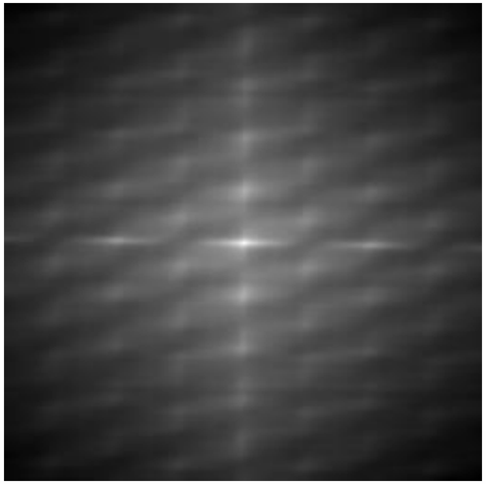


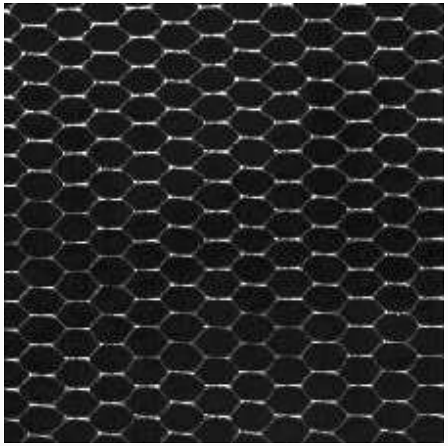
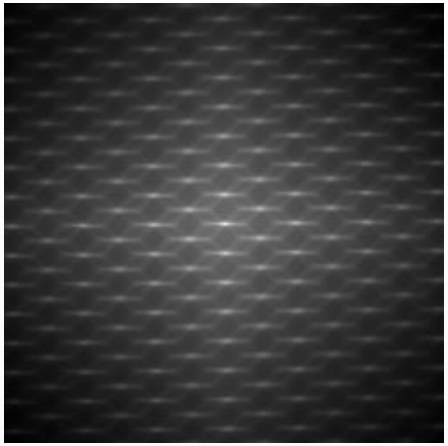
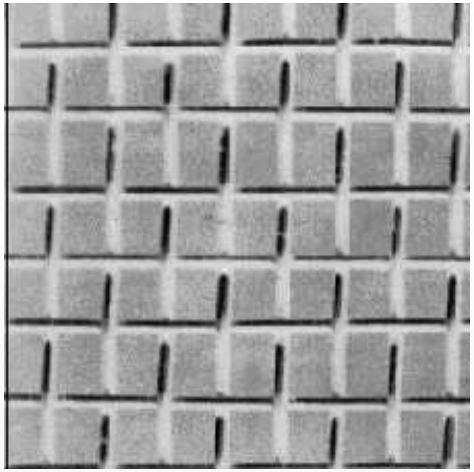
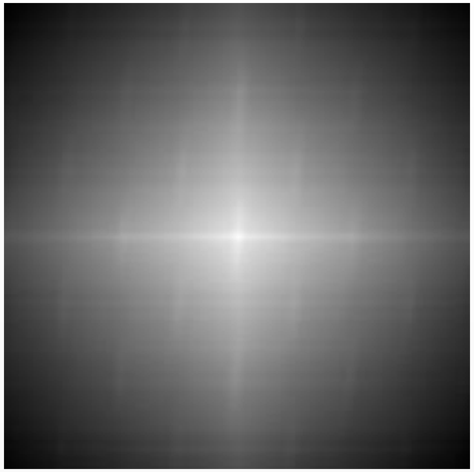
Principle: a coarse pattern texture for the same shift value shows greater autocorrelation than a finer pattern one

Interpreting autocorrelation

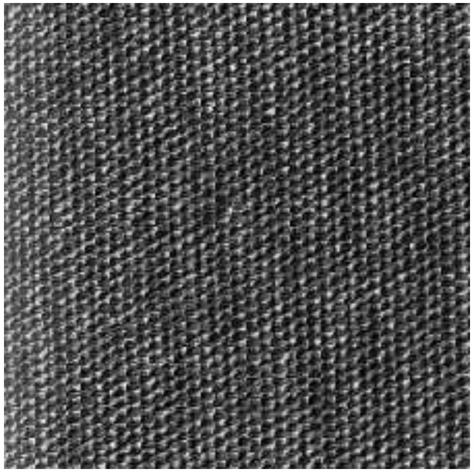
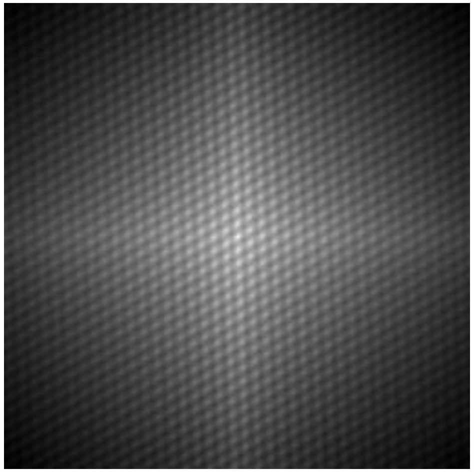
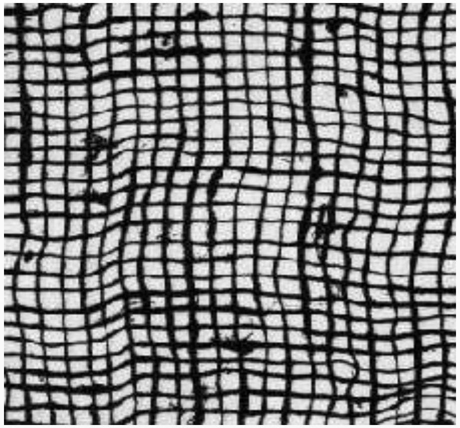
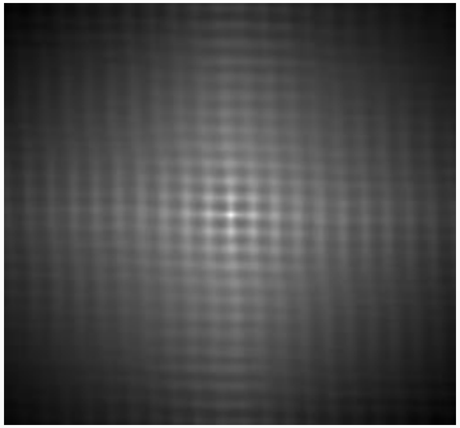
- Coarse texture → function drops off slowly
- Fine texture → function drops off rapidly
- Regular textures → function will have peaks and valleys; peaks can repeat far away from [0, 0]
- Random textures → only peak at [0, 0]; breadth of peak gives the size of the texture

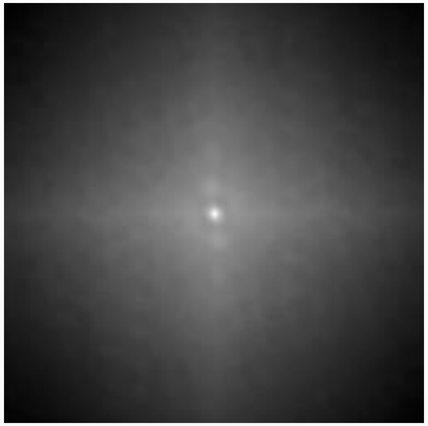
Autocorrelation

Autocorrelation

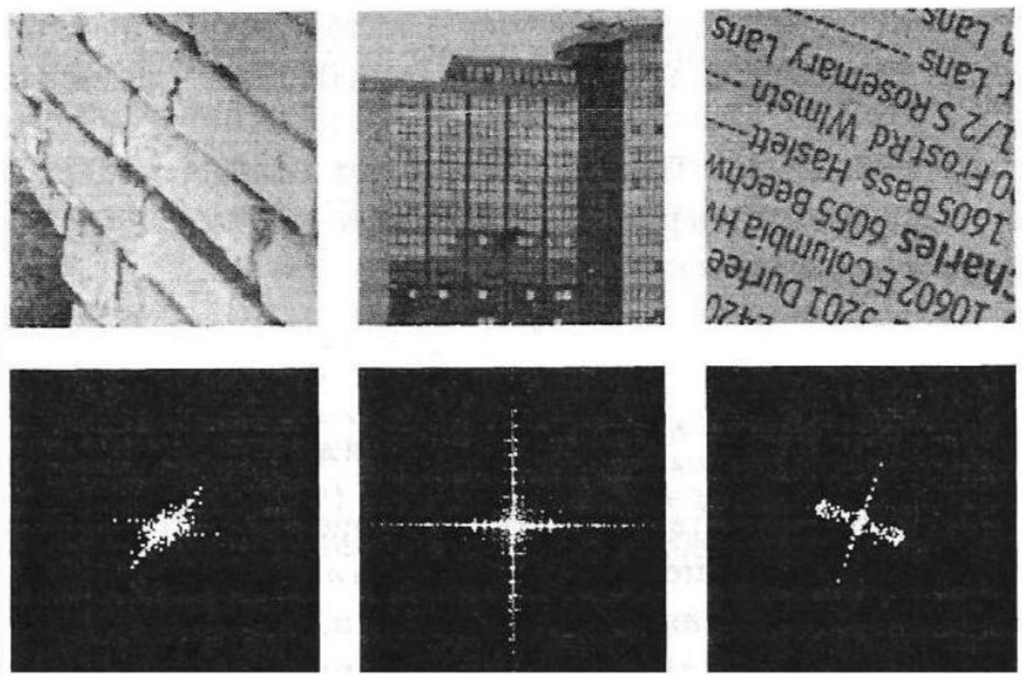


Autocorrelation calculation the Fourier domain

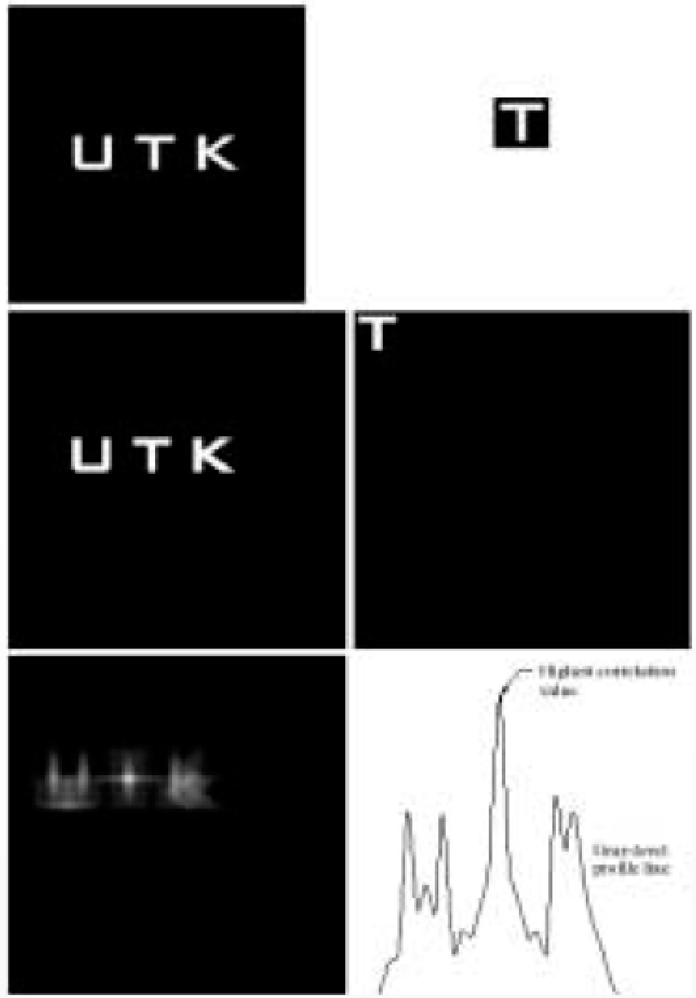
- Wiener-Khinchin Theorem
  - Input image: $I(x, y)$
  - Fourier transform: $\{X(\omega_1, \omega_2)\} = \mathrm{DFT}\{I(x, y)\}$
  - Power spectrum: $P_{XX}(\omega_1, \omega_2) = X(\omega_1, \omega_2) \cdot X^*(\omega_1, \omega_2)$=$|X(\omega_1, \omega_2)|^2$
  - Autocorrelation: inverse Fourier transform of the power spectrum: $\{R_{II}(\Delta x, \Delta y)\} = \mathrm{IDFT}\{P_{XX}(\omega_1, \omega_2)\}$

Fourier domain analysis

- Power spectrum: $X\{\omega_1, \omega_2\} \cdot X^*\{\omega_1, \omega_2\}$= =$|X\{\omega_1, \omega_2\}|^2$
- Concentrated power → regularity
- High frequency power → fine texture
- Directionality → directional texture



Correlation (pattern recognition)



Textures – image features

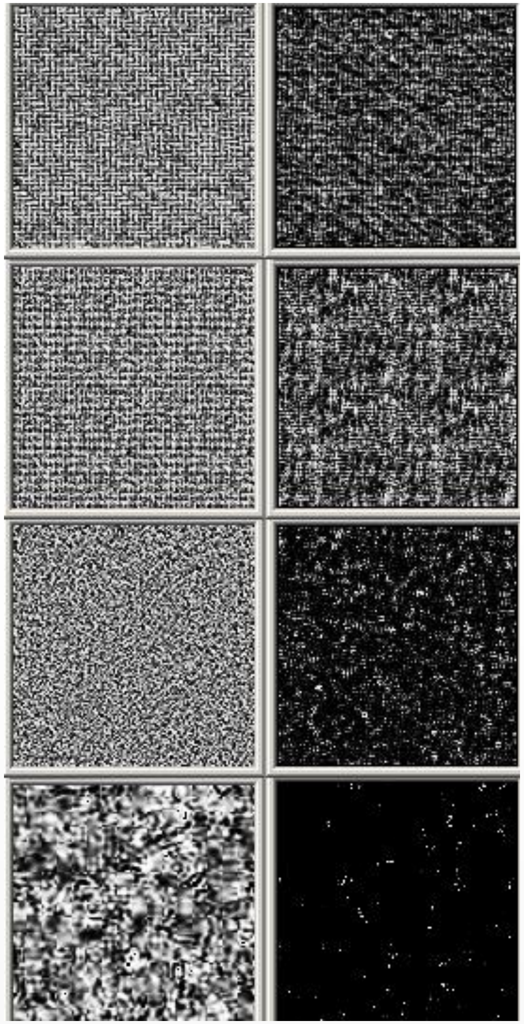
- Edge detection based procedures

E(j,k) = binary edge image obtained
by some edge detector (eg. Sobel)

Use low threshold for binarization

Measure of local edge content

$$T(j,k)=\frac{1}{(2w+1)^2}\sum_{m=-w}^{w}\sum_{n=-w}^{w}E(j+m,k+n)$$



Laws filters

- Enhancing micro-structure of the texture
- Main elements:
  - Averaging
  - Edges
  - Points

$$L_3 = \frac{1}{6}\begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \qquad E_3 = \frac{1}{2}\begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \qquad S_3 = \frac{1}{2}\begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix}$$

level detection filter — edge detection filter — spot detection filter

Laws filters

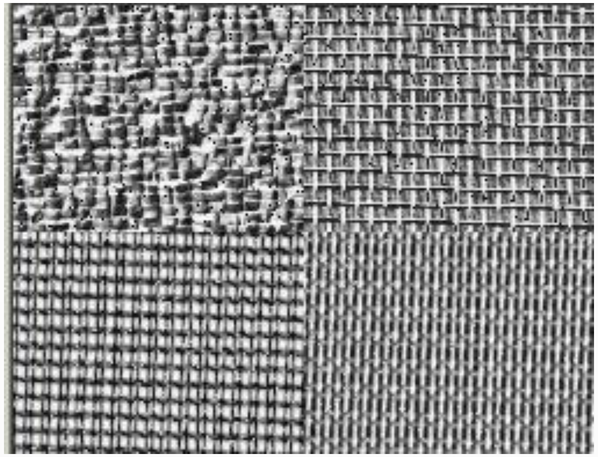
$$H_1 = L_3 L_3^T = \frac{1}{36}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \quad H_2 = L_3 E_3^T = \frac{1}{12}\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \quad H_3 = L_3 S_3^T = \frac{1}{12}\begin{bmatrix} 1 & -2 & 1 \\ 2 & -4 & 2 \\ 1 & -2 & 1 \end{bmatrix}$$

$$H_4 = E_3 L_3^T = \frac{1}{12}\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \quad H_5 = E_3 E_3^T = \frac{1}{4}\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix} \quad H_6 = E_3 S_3^T = \frac{1}{4}\begin{bmatrix} 1 & -2 & 1 \\ 0 & 0 & 0 \\ -1 & 2 & -1 \end{bmatrix}$$

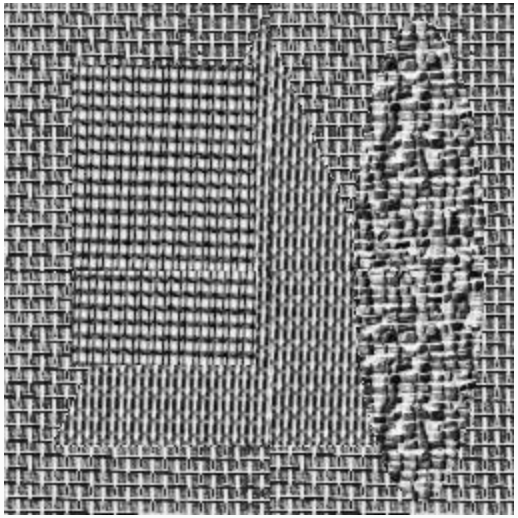
$$H_7 = S_3 L_3^T = \frac{1}{12}\begin{bmatrix} 1 & 2 & 1 \\ -2 & -4 & -2 \\ 1 & 2 & 1 \end{bmatrix} \quad H_8 = S_3 E_3^T = \frac{1}{4}\begin{bmatrix} 1 & 0 & -1 \\ -2 & 0 & 2 \\ 1 & 0 & -1 \end{bmatrix} \quad H_9 = S_3 S_3^T = \frac{1}{4}\begin{bmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{bmatrix}$$

Texture segmentation - Laws

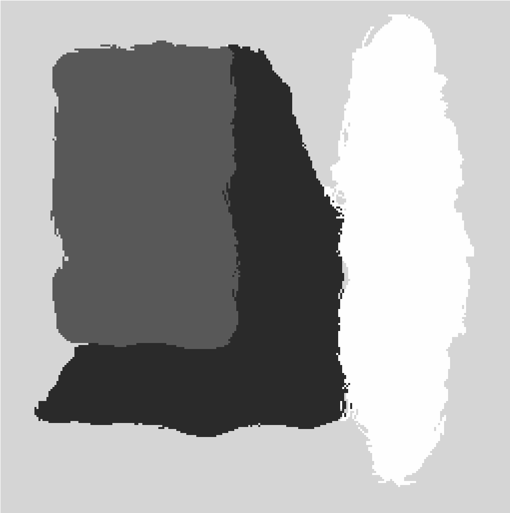
- Training step, thereafter recognizing the trained textures
- Utilizing Law matrices



Training image

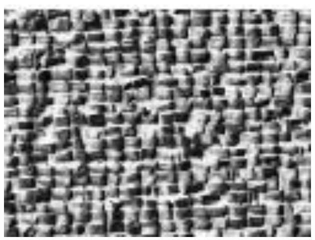


Input test image



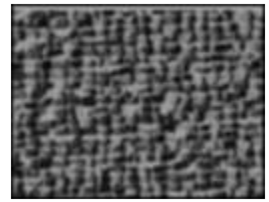
Ground truth for the test image

Learning a training texture model



$F: h \times w$ training texture sample

Convolution with H_1 kernel

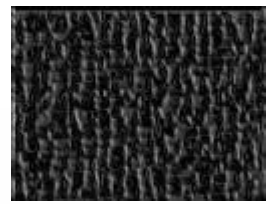


$K_1 = F \otimes H_1$

Squared averaging

$$M_1 = \frac{1}{hw} \sum_{x,y} K_1^2(x,y)$$

Convolution with H_2 kernel



$K_2 = F \otimes H_2$

$$M_2 = \frac{1}{hw} \sum_{x,y} K_2^2(x,y)$$

Convolution with H_9 kernel

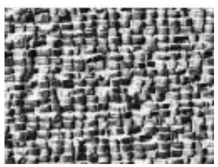
$K_9 = F \otimes H_9$

$$M_9 = \frac{1}{hw} \sum_{x,y} K_1^2(x,y)$$

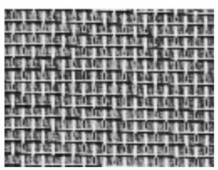
Laws filter– training phase

- Each training texture j is represented by 9 scalars: $M_1^j \ldots M_9^j$

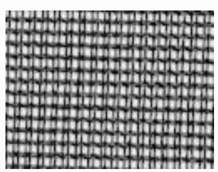
$$M_i^j = \frac{1}{hw}\sum_{x,y}\left(K_i^j(\mathrm{x},\mathrm{y})\right)^2,\ \text{where } i = 1, \ldots, 9, j = 1, \ldots 4, \quad \text{and} \quad K_i^j = F_j \otimes K_i$$



$M_1^1, M_2^1, M_3^1, M_4^1, M_5^1, M_6^1, M_7^1, M_8^1, M_9^1$



$M_1^2, M_2^2, M_3^2, M_4^2, M_5^2, M_6^2, M_7^2, M_8^2, M_9^2$

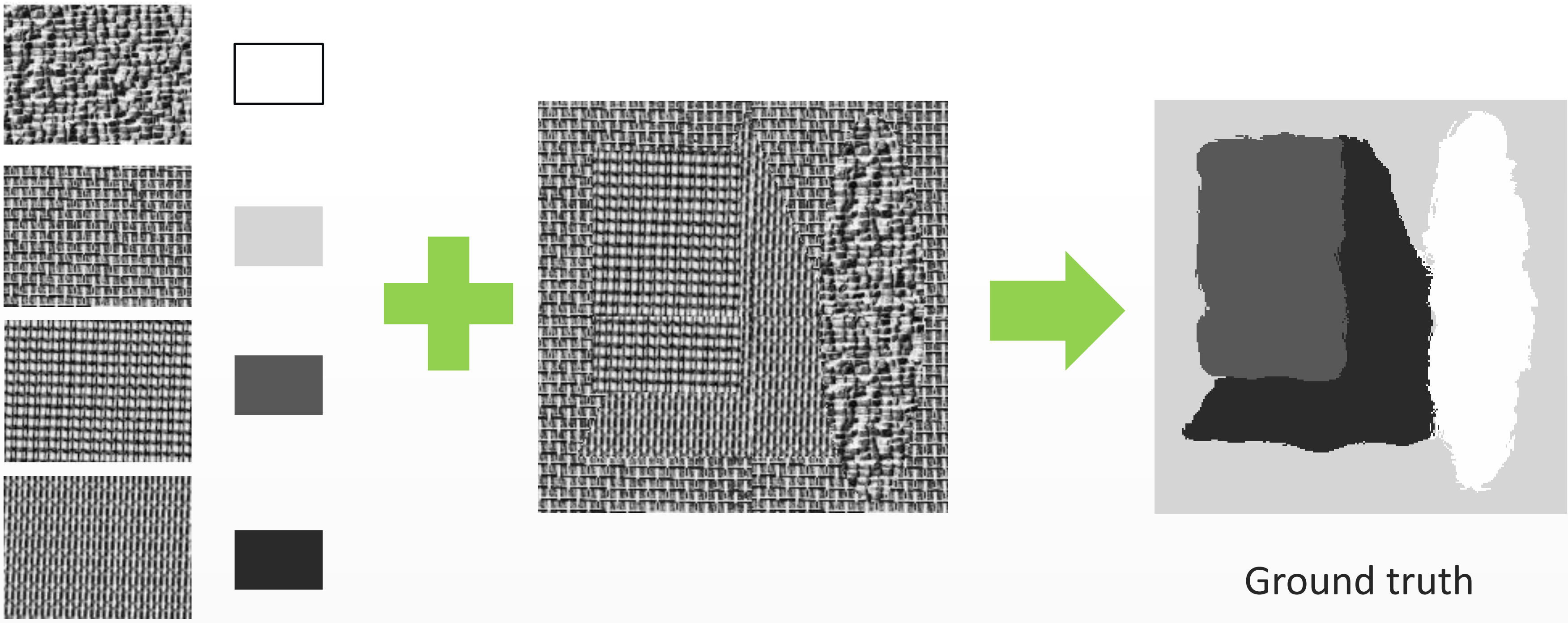


$M_1^3, M_2^3, M_3^3, M_4^3, M_5^3, M_6^3, M_7^3, M_8^3, M_9^3$

$M_1^4, M_2^4, M_3^4, M_4^4, M_5^4, M_6^4, M_7^4, M_8^4, M_9^4$

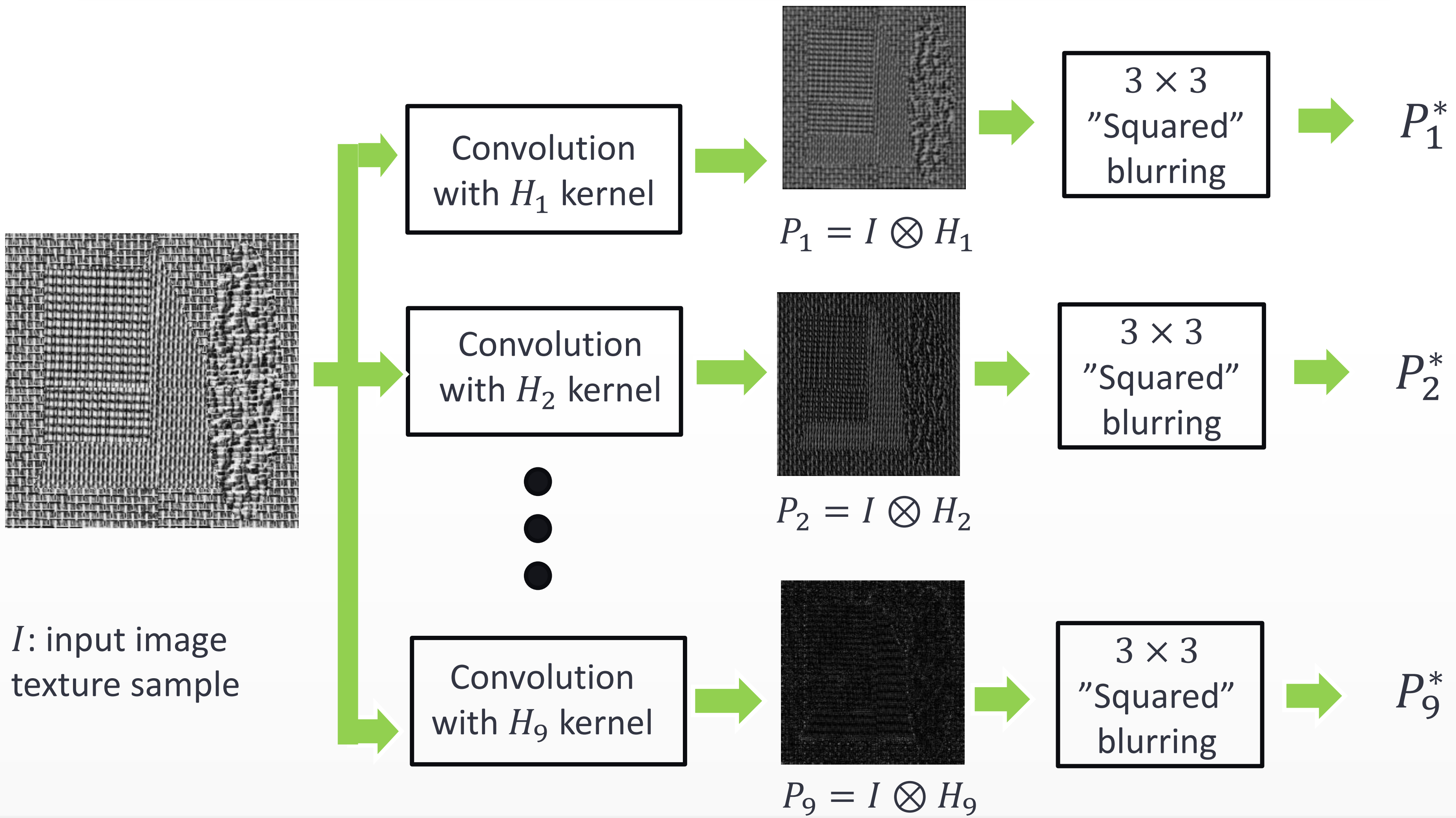
Laws filter– recognition phase

- Input image: consists of arbitrary regions of pre-trained textures



Ground truth

Laws filter– recognition phase



I: input image texture sample

Laws filter– recognition phase

- Pixel level decision of the input map

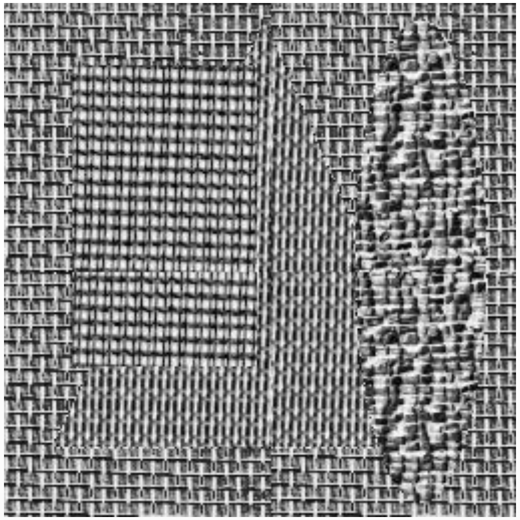
$$\mathrm{ClassMap}(x,y) = \underset{j=1\ldots4}{\mathrm{argmin}} \sum_{i=1\ldots9} \left| P_i^*(x,y) - M_i^j \right|$$

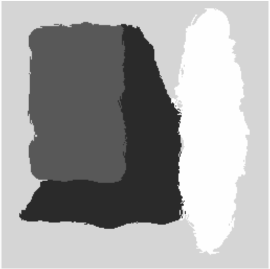
where

$$P_i^*(x,y) = \frac{1}{9} \sum_{r=x-1}^{x+1} \sum_{s=y-1}^{y+1} P_i^2(x+r, y+s)$$

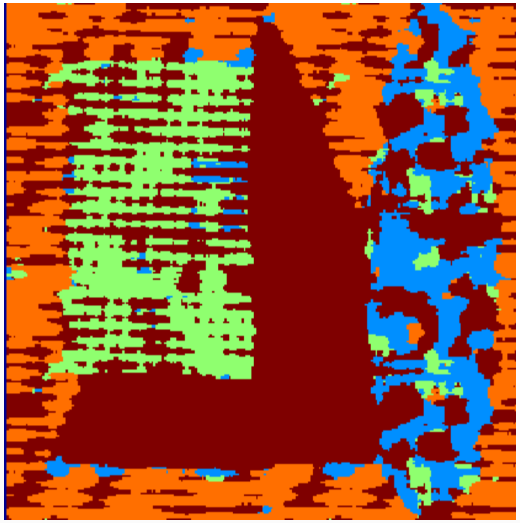
Texture segmentation result

- Output „winner class” maps for the four textures – enhanced with some morphology





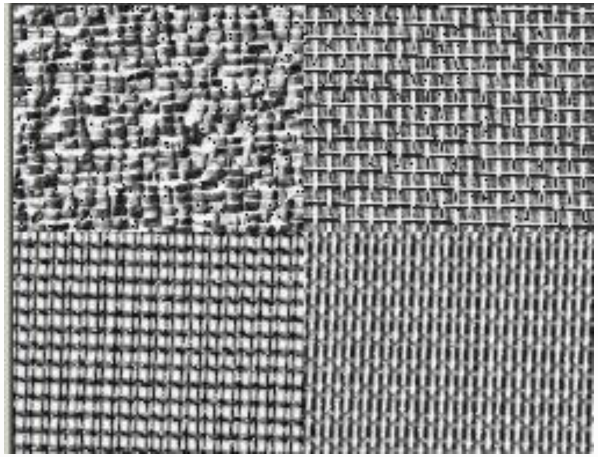
Ground truth

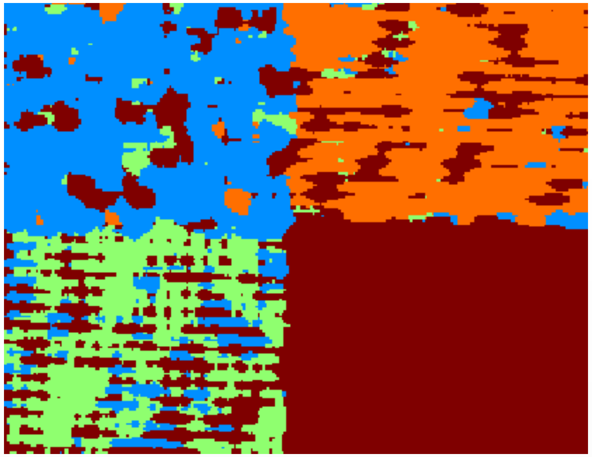


Laws segmentation results

Texture segmentation result

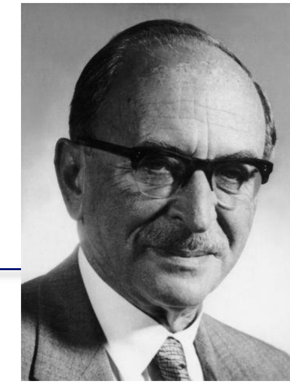
- Output „winner class” maps for the four textures – enhanced with some morphology

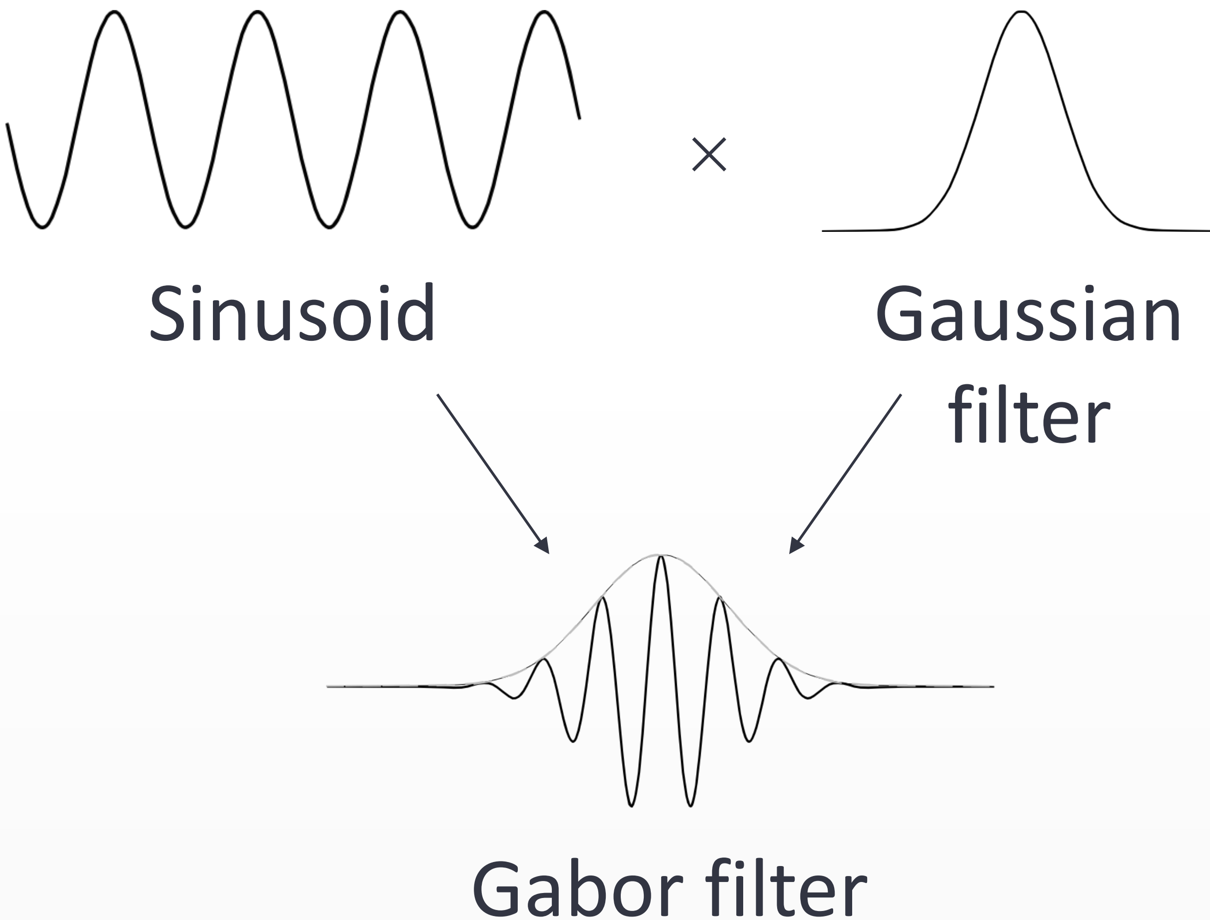




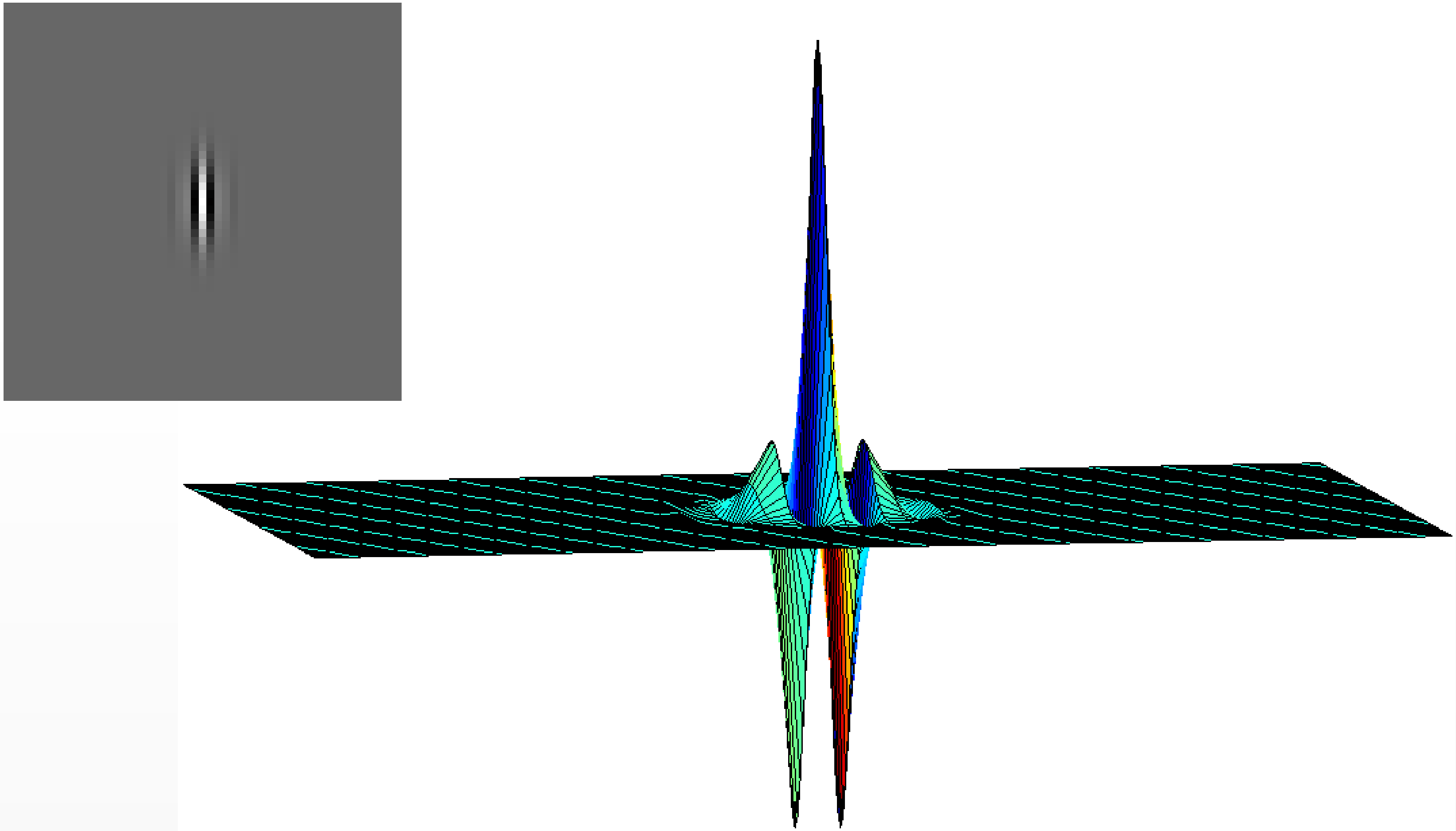
Laws segmentation results

Gabor filters – 1D illustration



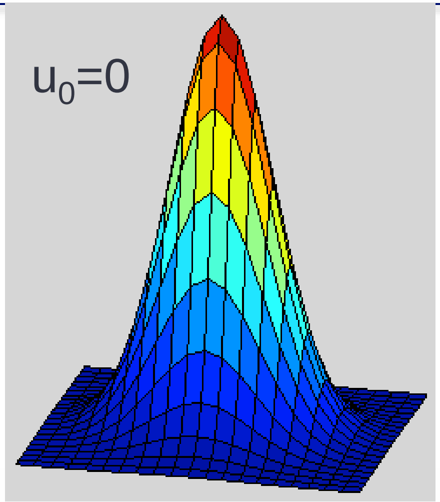


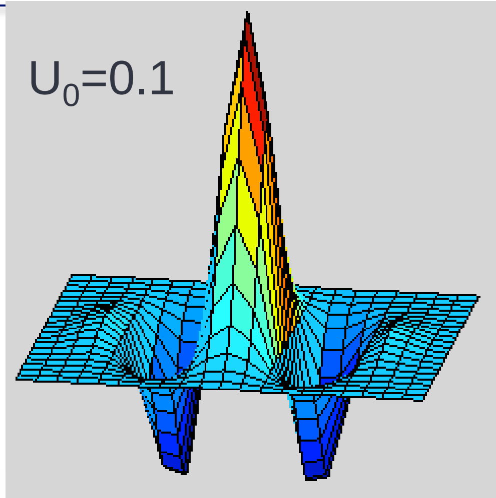
Gabor filters- 2D kernel example

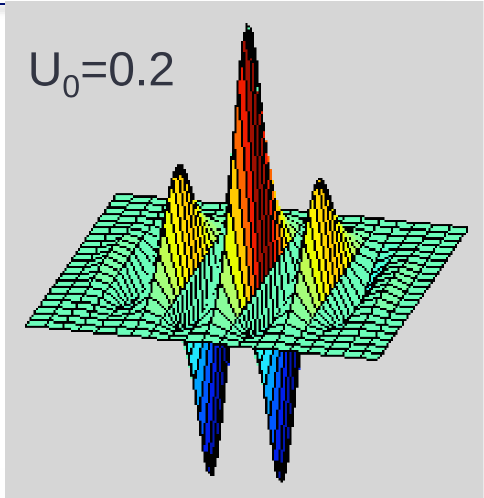


2D - Gabor wavelets

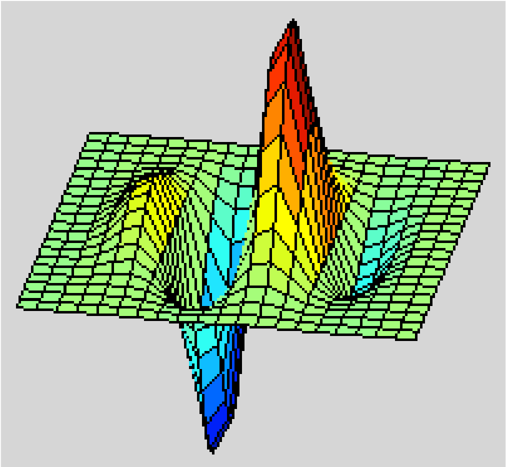
$$\psi_c(x,y) = e^{-\frac{x^2+y^2}{2\sigma^2}} \cos(2\pi u_0 x)$$

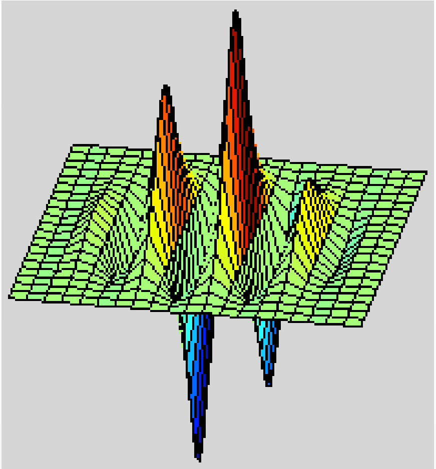


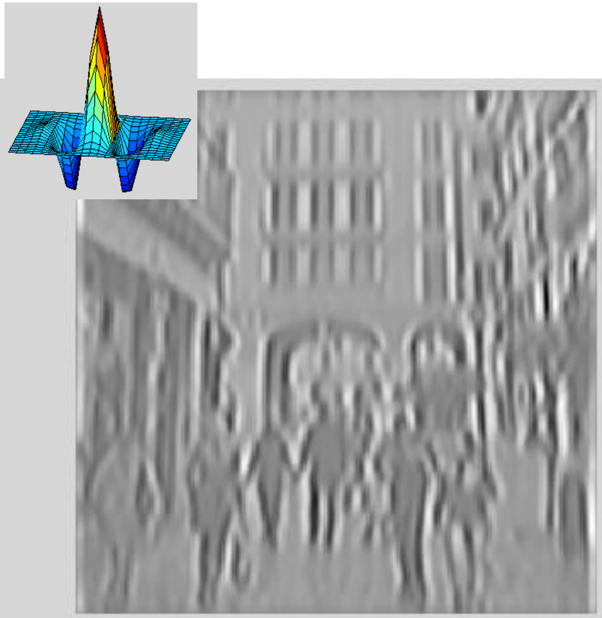




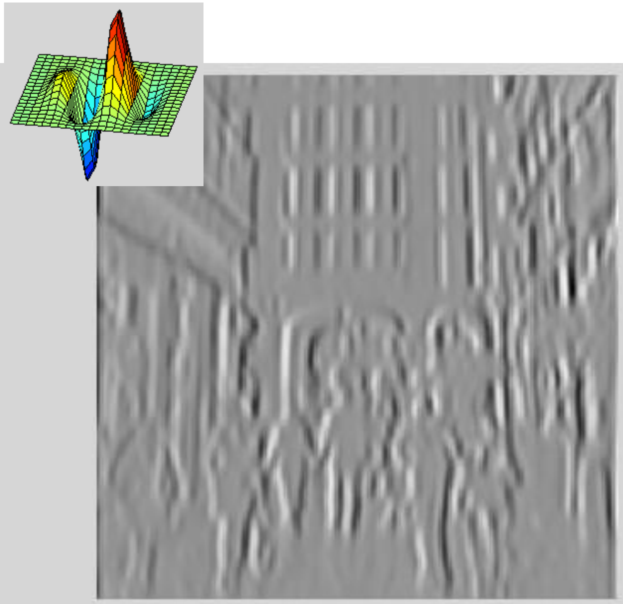
$$\psi_s(x,y) = e^{-\frac{x^2+y^2}{2\sigma^2}} \sin(2\pi u_0 x)$$



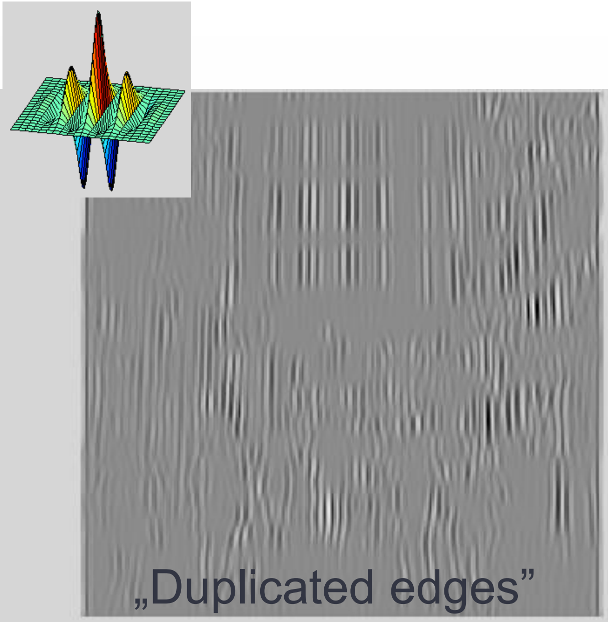




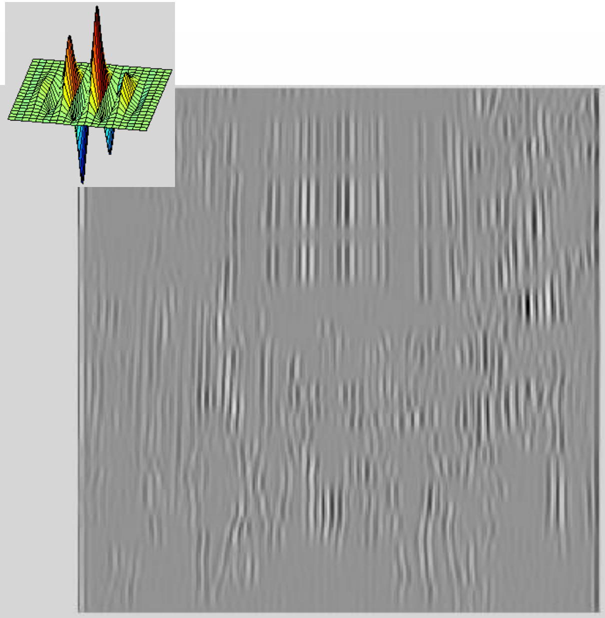
Salient bright thin vertical lines



Dark-bright transitions in horizontal direction



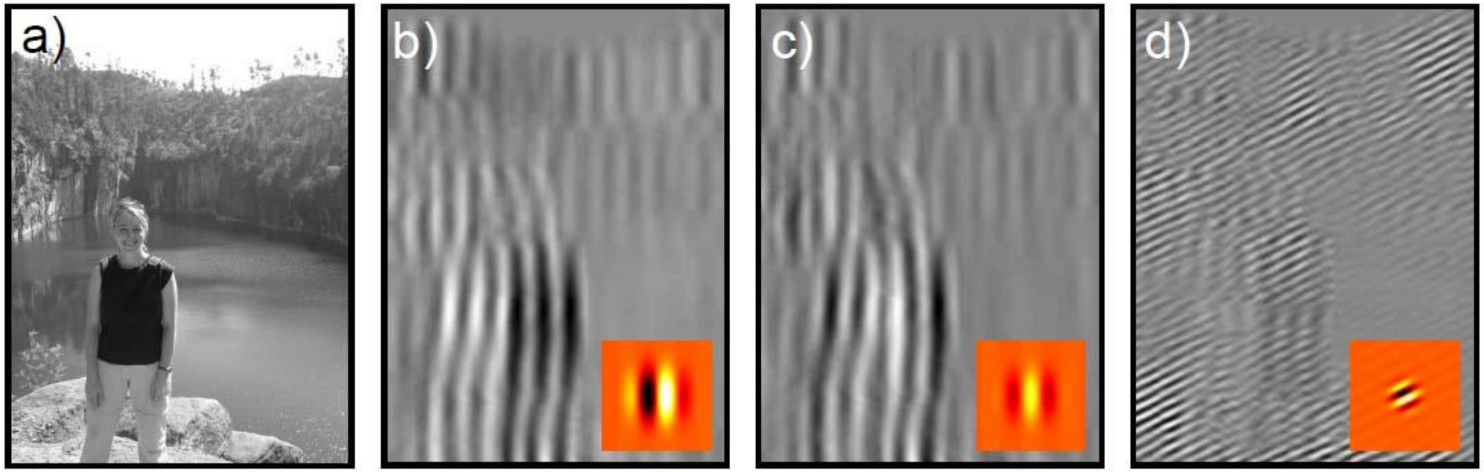
„Duplicated edges”



Application of Gabor filters in image processing

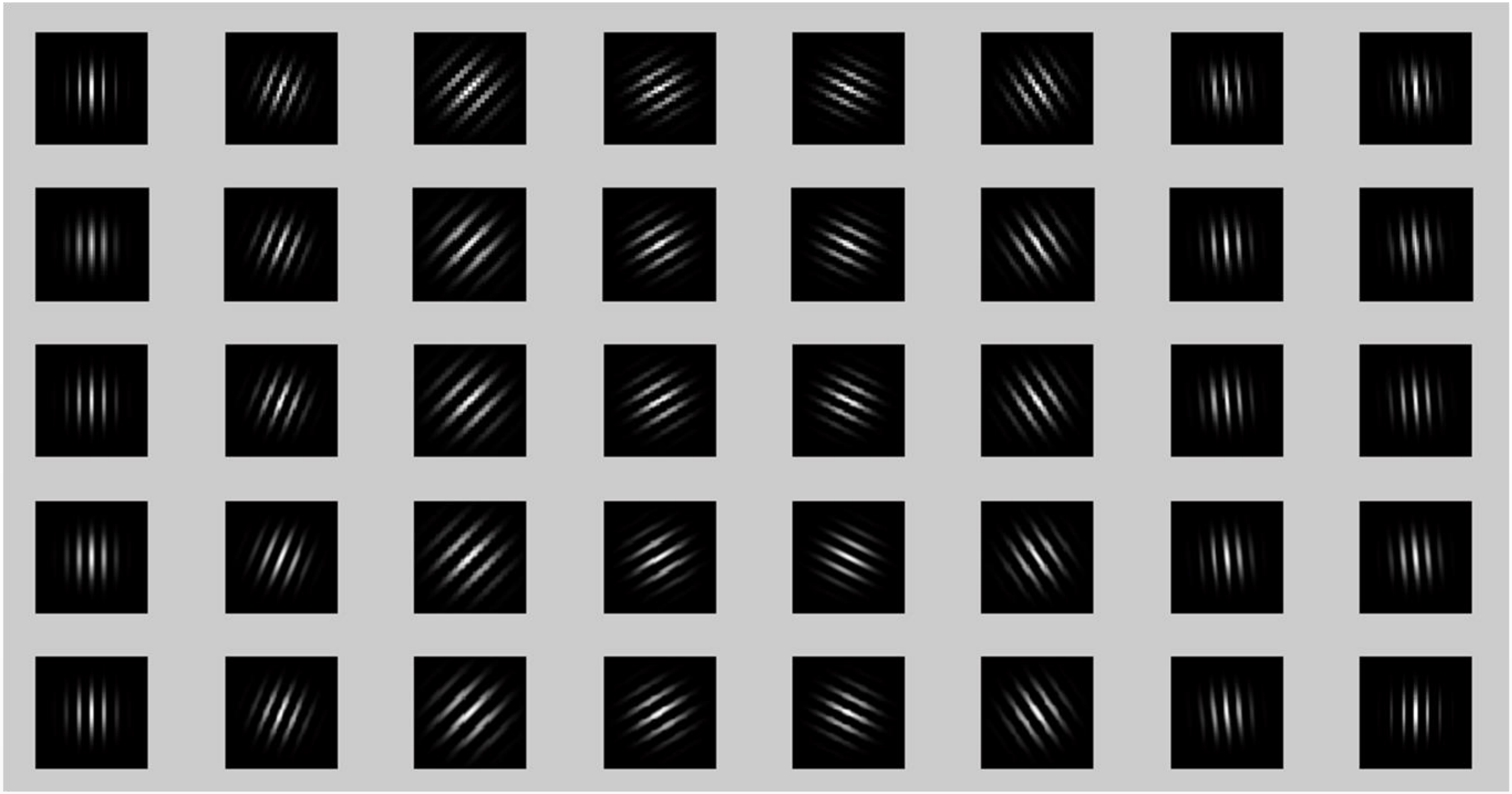
- Gabor filters can selectively highlight specific image elements according to their appropriately set frequency, orientation and phase parameters
- Invariant for additive changes of illumination (in case of asymmetric sinusoid functions)
- Motivation: vision mechanism of mammals – one of the first processing operations of visual stimuli in the brain

Application of Gabor filters in image processing



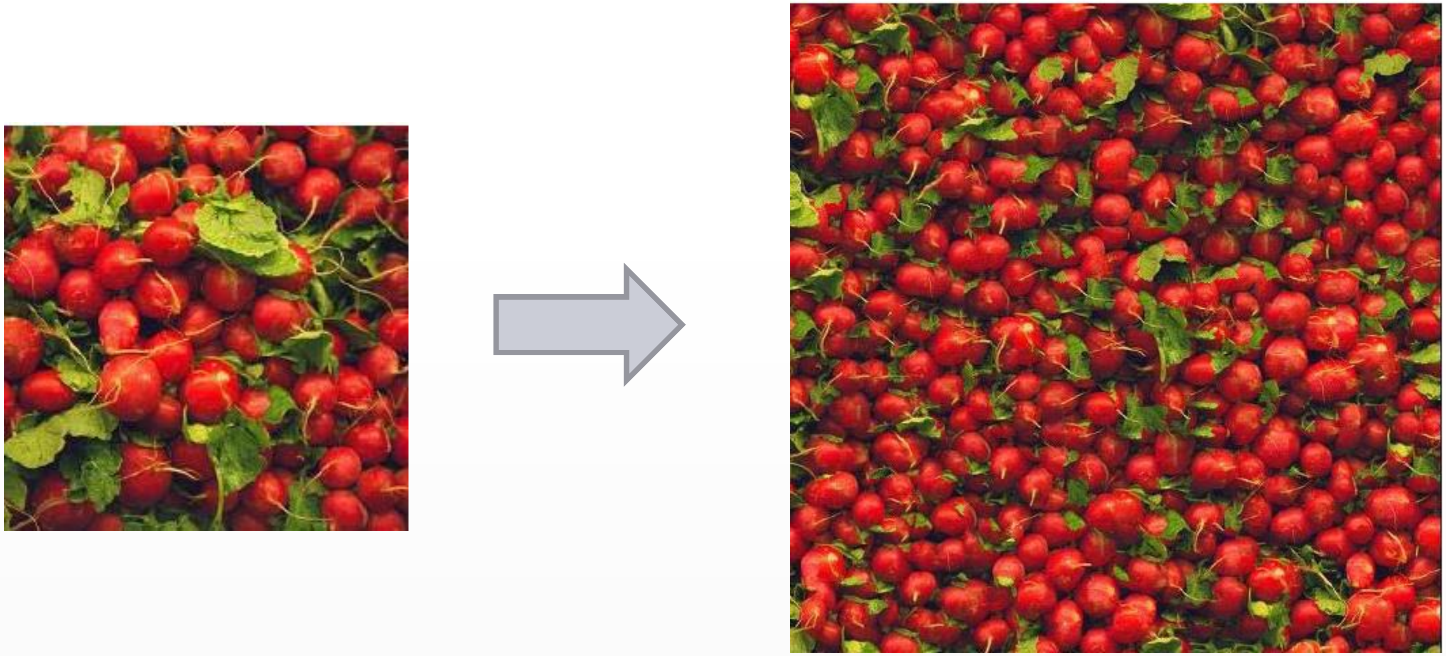
a) Input image. b) Output of a low frequency, horizontal, asymetric Gabor filter. c) Output of a low frequency, horizontal, symetric Gabor filter d) Output of a diagonal Gabor filter

Direction selective Gabor filter bank



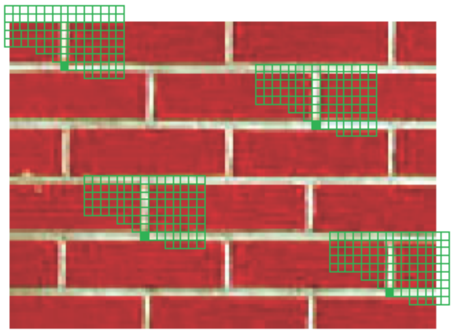
Texture Synthesis

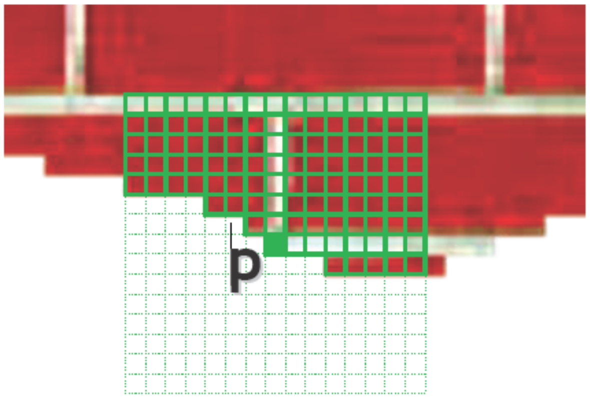
- Given a small sample, generate larger realistic versions of the texture



Alexei A. Efrosand Thomas K. Leung, "Texture Synthesis by Non-parametric Sampling,"Proc. International Conference on Computer Vision (ICCV), 1999.

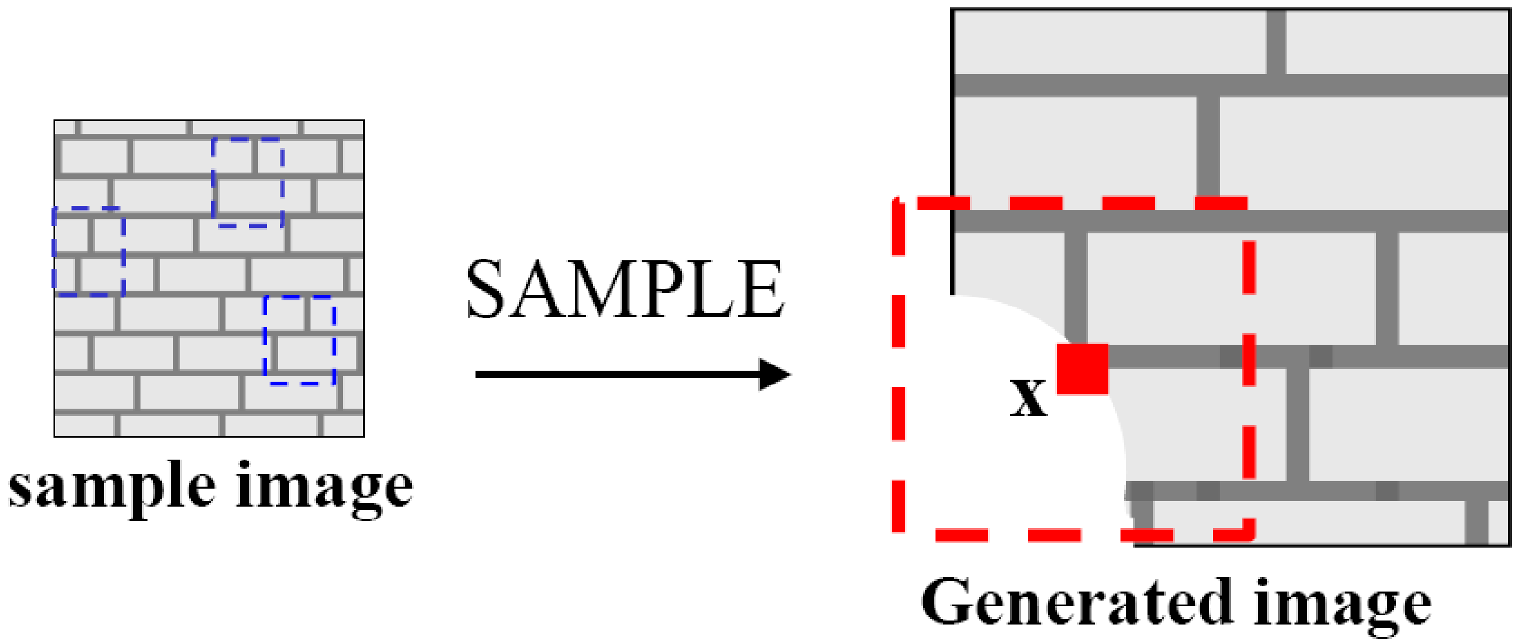
Synthesizing One Pixel





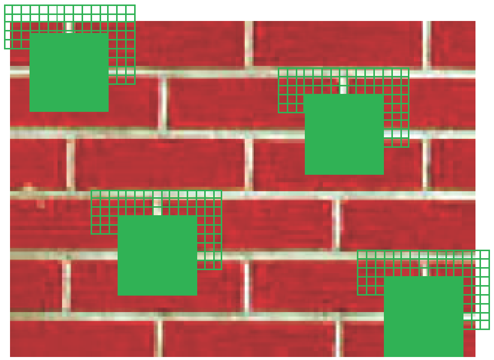
- What is $P(x|\text{neighborhood of pixels around } x)$?
  - Find all the windows in the image that match the neighborhood– consider only pixels in the neighbourhood that are already filled in
  - To synthesize **x**
    - pick one matching window at random
    - assign **x** to be the centerpixel of that window

Really Synthesizing One Pixel

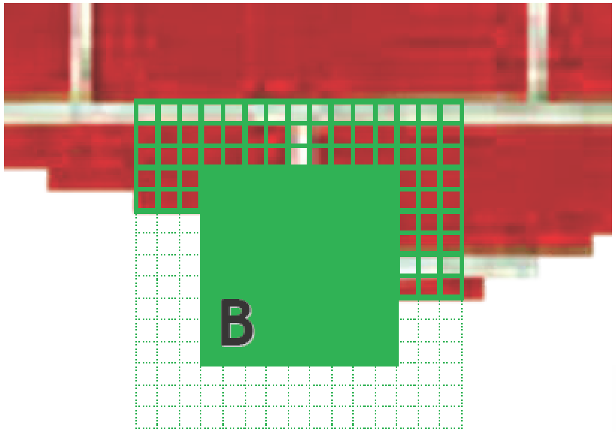


- An exact neighborhood match might not be present
- So we find the **best** matches using SSD error and randomly choose between them, preferring better matches with higher probability

Block-based texture synthesis



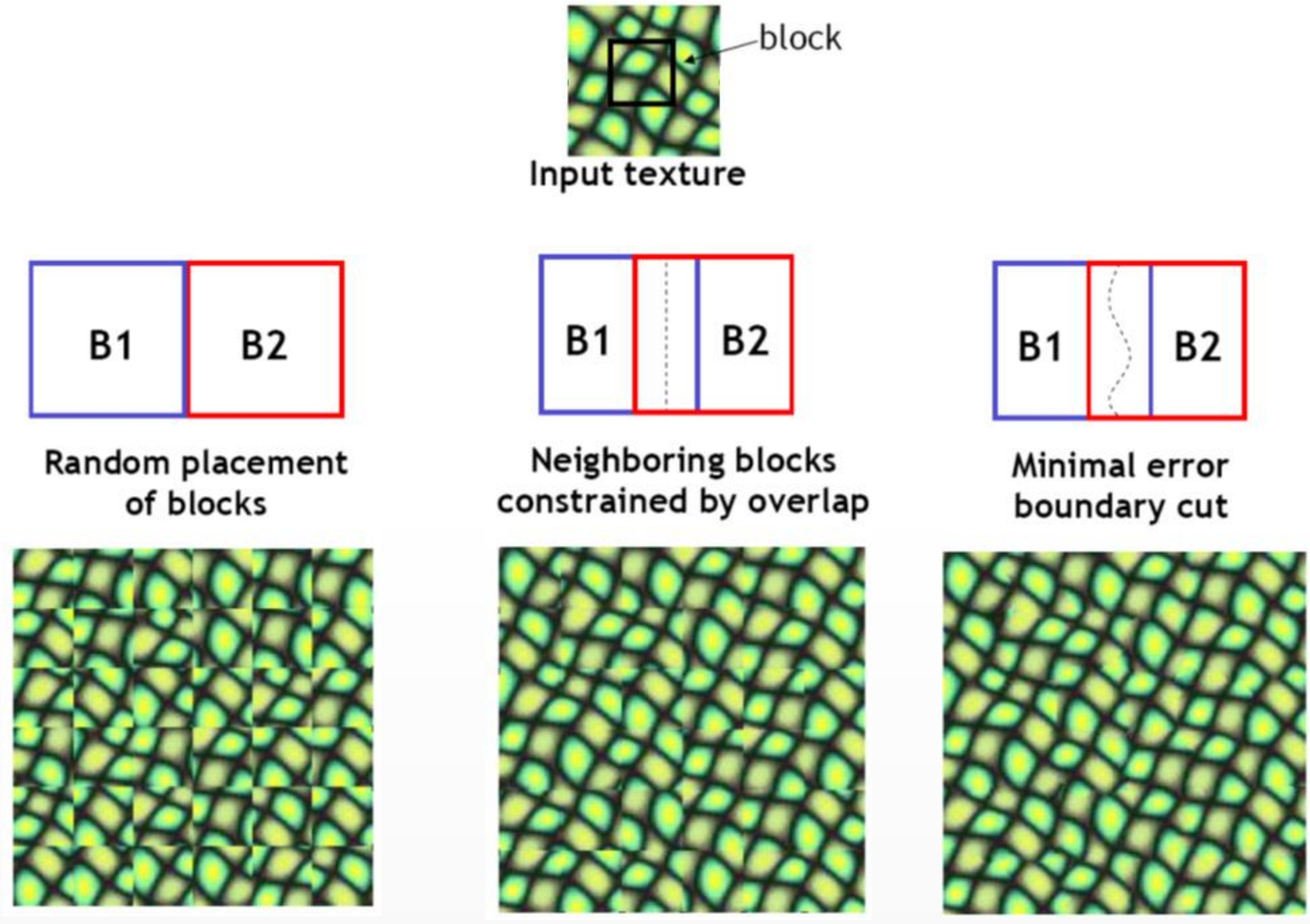
Input image

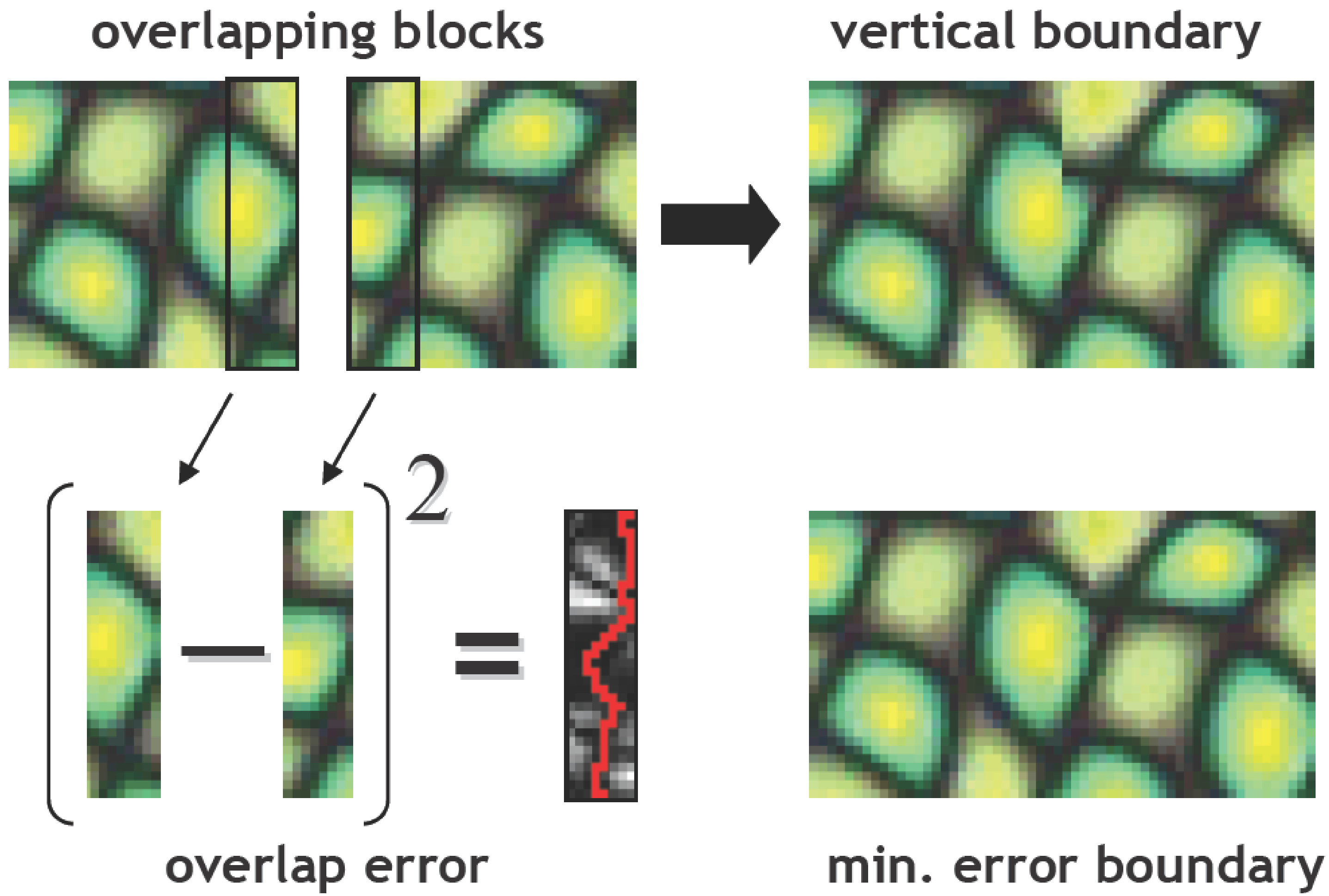


Synthesizing a block

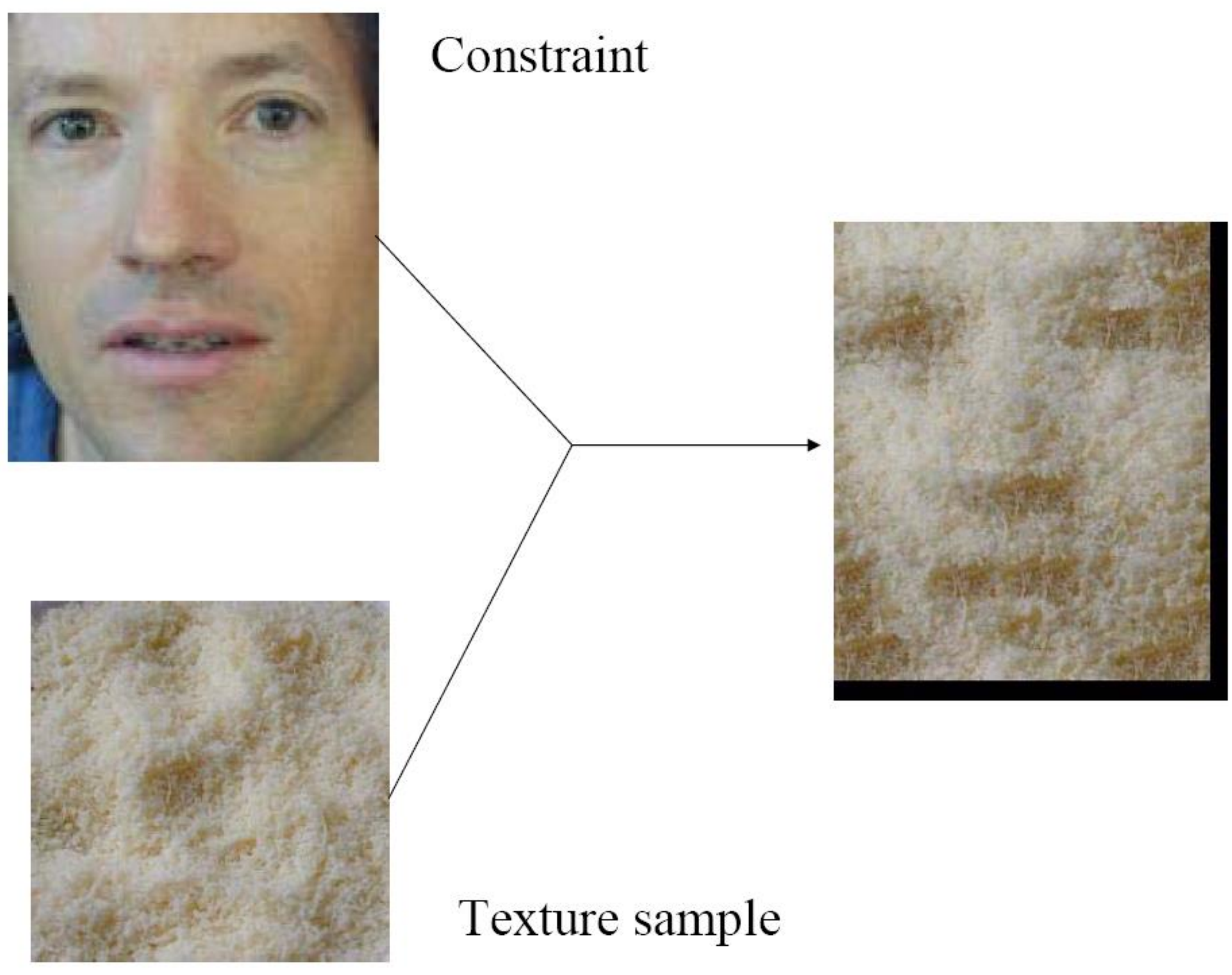
- **<u>Observation</u>**: neighbor pixels are highly correlated
- **<u>Idea:</u> unit of synthesis = block**
  - Exactly the same but now we want P(**B**|N(**B**))
  - Much faster: synthesize all pixels in a block at once

Image Quilting for Texture Synthesis and Transfer', Efros& Freeman, SIGGRAPH, 2001.


block
Input texture
B1
B2
Random placement of blocks
B1
B2
Neighboring blocks constrained by overlap
B1
B2
Minimal error boundary cut


overlapping blocks
vertical boundary
2
overlap error
min. error boundary

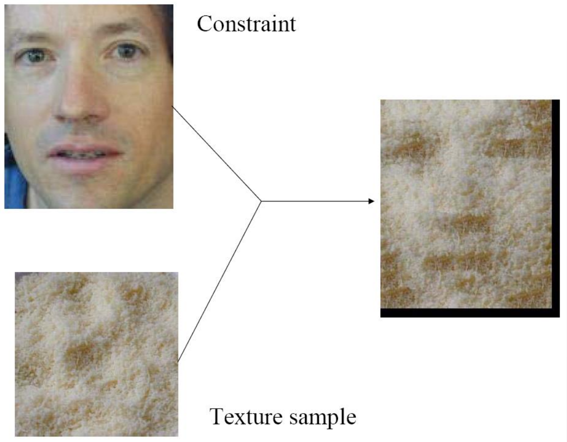
Texture Transfer



Texture Transfer

- Each patch satisfy a desired correspondence map C as well as satisfy the texture synthesis requirements.
- C: a spatial map of some corresponding quantity over both the texture source image and a controlling target image.
  - E.g. image intensity, blurred image intensity, local image orientation angles, or other derived quantities.

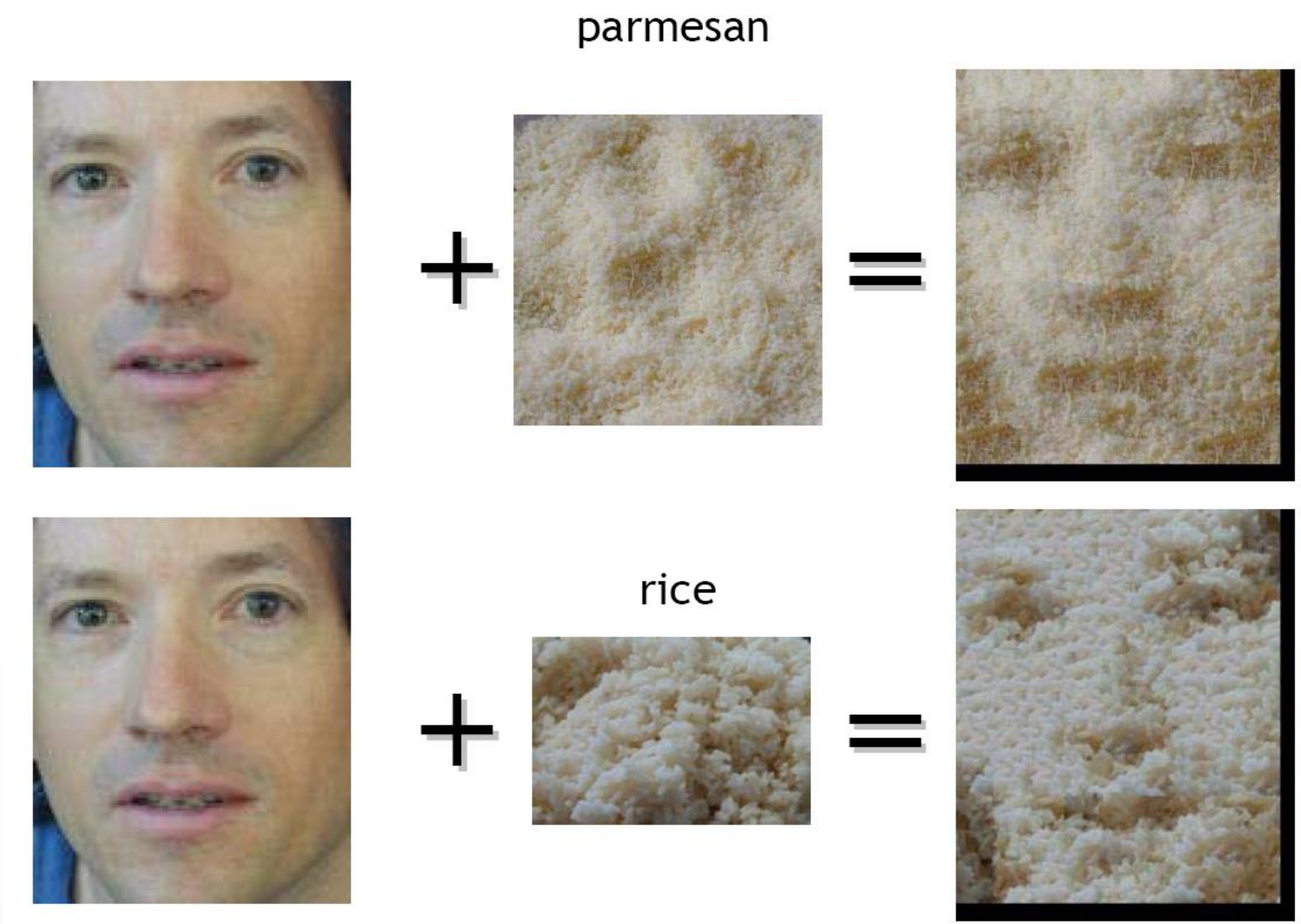
Here: bright patches of face and bright patches of rice are defined to have a low correspondence error.

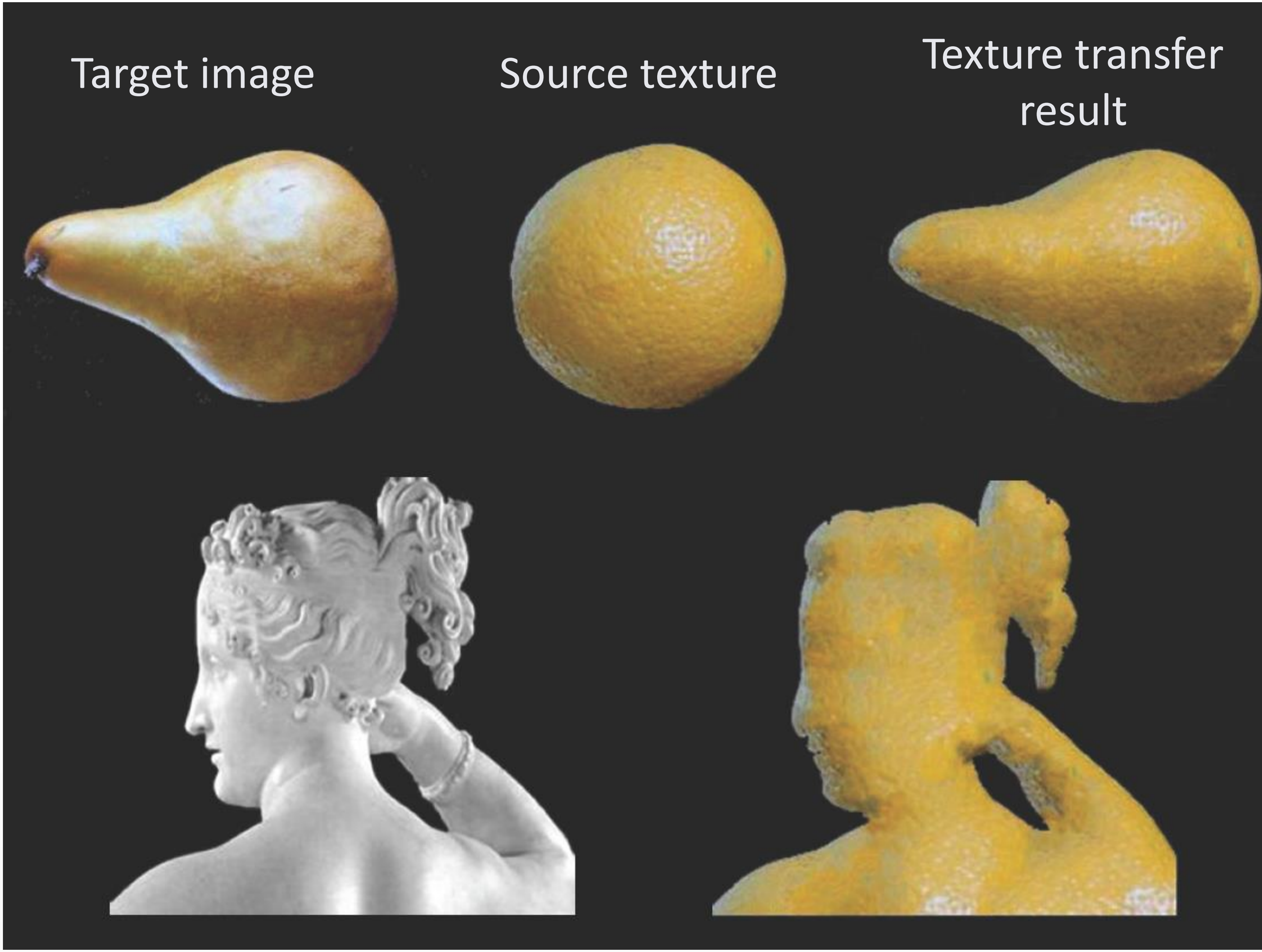


Texture Transfer

- Take the texture from one image and "paint" it onto another object

- Same algorithm as before with additional term
  - do texture synthesis on image1, create new image (size of image2)
  - add term to match intensity of image2


parmesan
rice


Target image
Source texture
Texture transfer result

Texture transfer