Mid Level Image Features
: Textures

Eun Yi Kim

Artificial Inteligence
& Computer Vision
Laboratory

INDEX

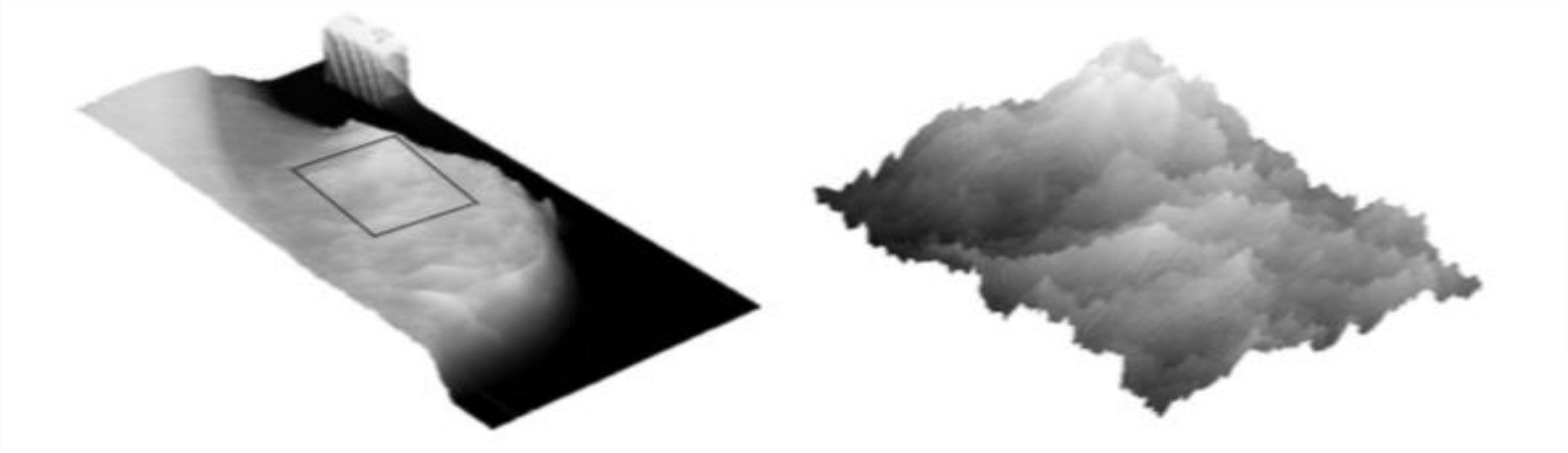
Artificial Inteligence
& Computer Vision
Laboratory

Texture

- Texture is a feature used to partition images into regions of interest and to classify those regions
- Texture provides information in the spatial arrangement of colors or intensities in an image.
- Texture is characterized by the spatial distribution of intensity levels in a neighborhood.

Texture

- Texture is a repeating pattern of local variations in image intensity
  - Texture cannot be defined for a point

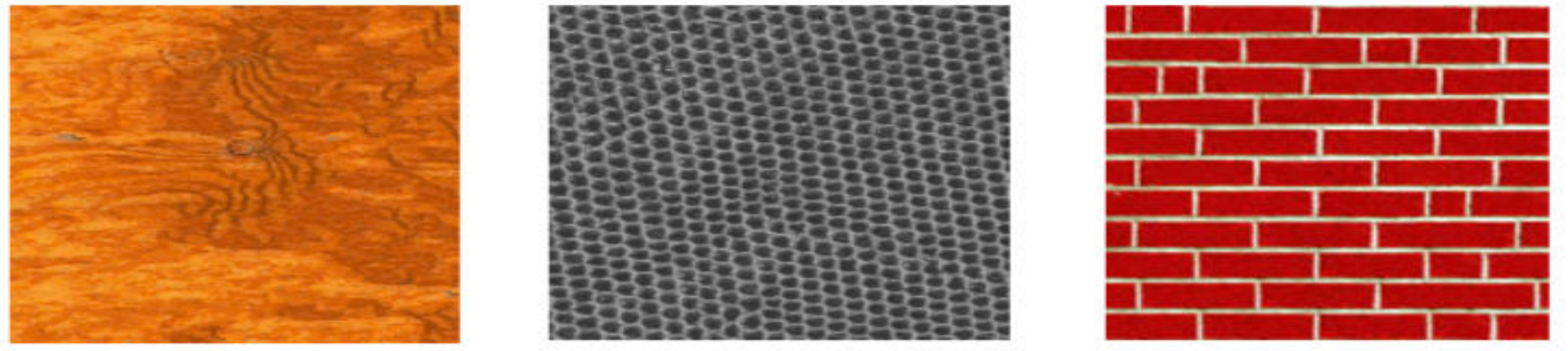


Texture

- For example, an image has a 50% black and 50% white distribution of pixels

- Three different images with the same intensity distribution, but with different textures

Texture

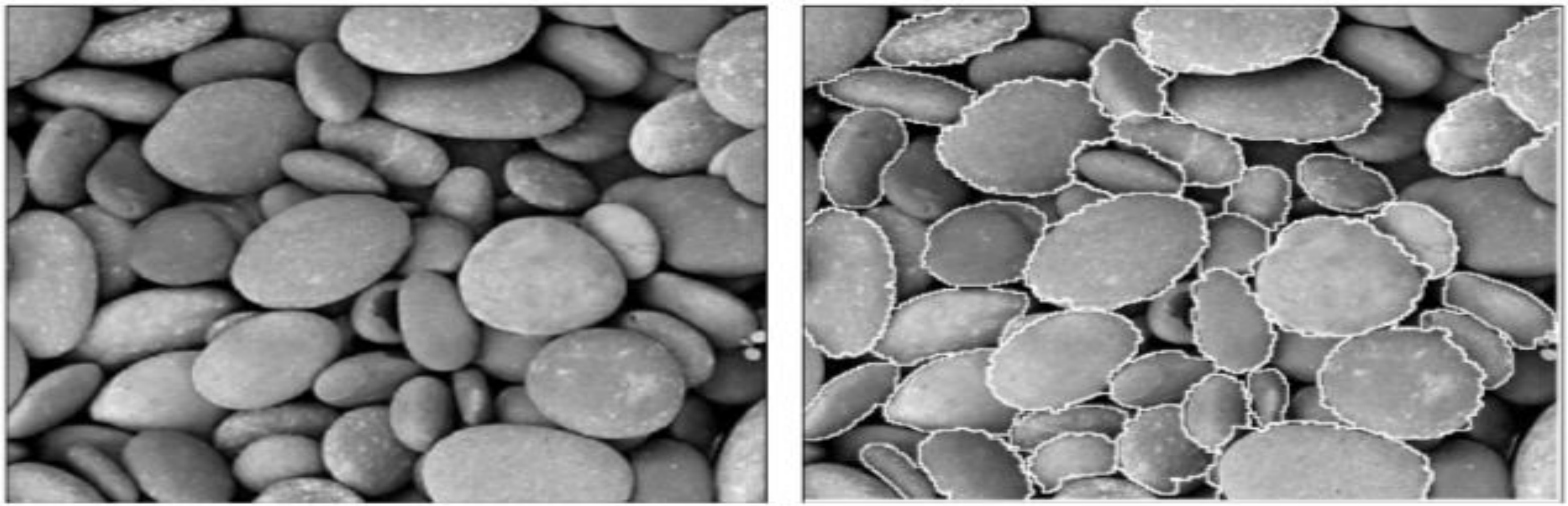


Understanding Texture

- There are three approaches to defining exactly what texture is:

1. **Structural** : texture is a set of primitive texels in some regular or repeated relationship.
2. **Statistical** : texture is a quantitative measure of the arrangement of intensities in a regions. This set of measurements is called a ***feature vector*.**
3. **Modeling** : texture modeling techniques involve constructing models to specify textures.

Structural approach to describing texture



http://vision.ai.uiuc.edu/~sintod/

Aspects of texture

- Size/Granularity
  - Sand versus pebbles versus boulders
- Directionality/Orientation
- Random or regular
  - Stucco versus bricks





Problem with Structural Approach

What/Where are the texels?

Extracting texels in real images may be difficult or impossible

Statistical Approach to Texture

- Characterize texture using statistical measures computed from gray-scale intensities (or colors) alone
- Less intuitive, but applicable to all images and computationally efficient
- Can be used for both classification of a given input texture and segmentation of an image into different texture regions

Texture Analysis

- There are two primary issues in texture analysis:
  - Texture classification
  - Texture segmentation

- Texture segmentation is concerned with automatically determining the boundaries between various texture regions in an image

- Texture classification is concerned with identifying a given textured regions from a given set of texture classes
  - Each of these regions has unique texture characteristics
  - Statistical methods are extensively used

Simple Statistical Texture Measure

Range

One of the simplest of the texture operator is the **range** or difference between maximum and minimum intensity values in a neighbor

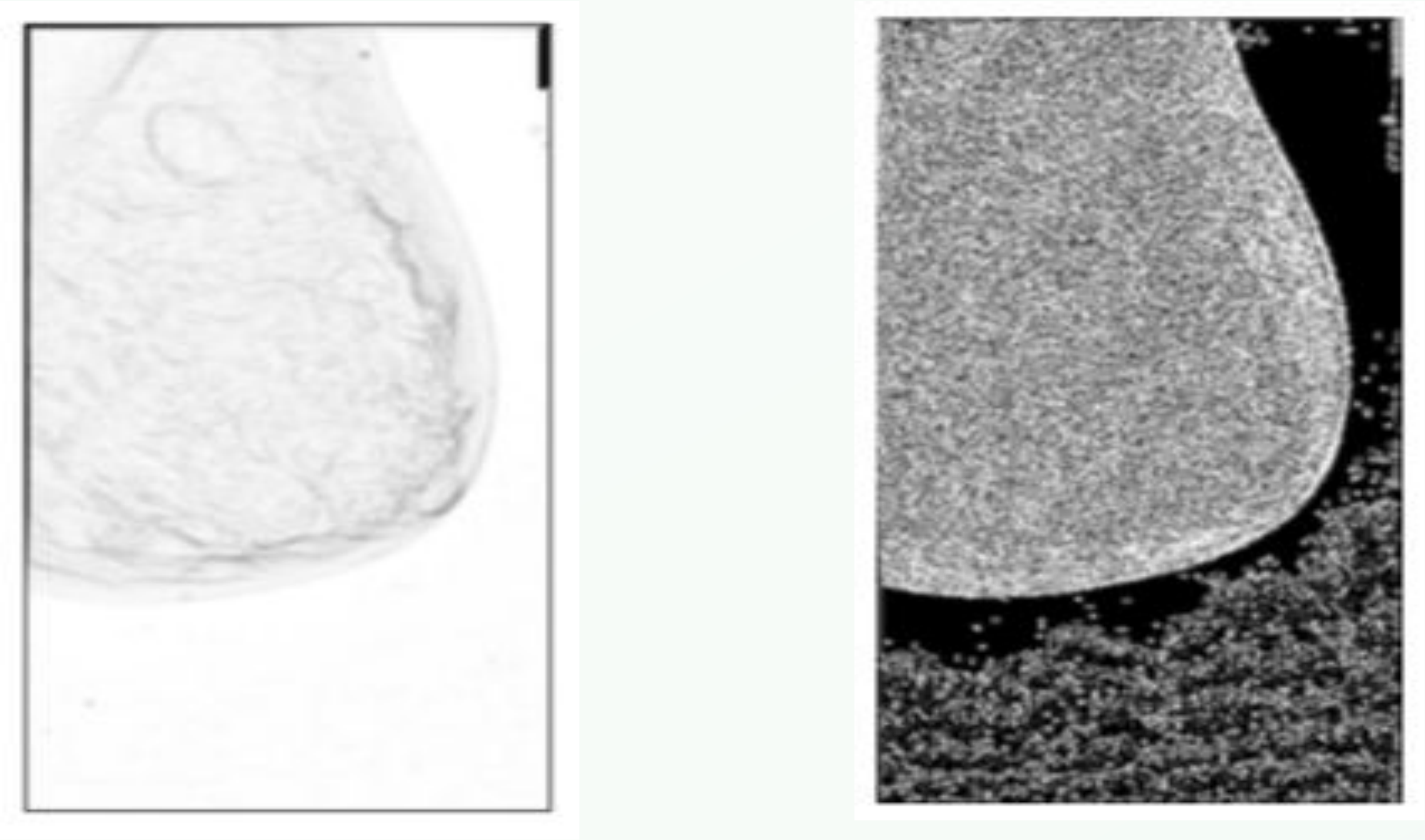
- The range operator converts the original image to one in which brightness represents texture

Variance

Another estimator of texture is the **variance** in neighborhood regions

- This is the sum of the squares of the differences between the intensity of the central pixel and its neighbors

Examples: Range and Variance



Quantitative Texture Measures

- Numeric quantities or statistics that describe a texture can be calculated from the intensities (or colors) themselves

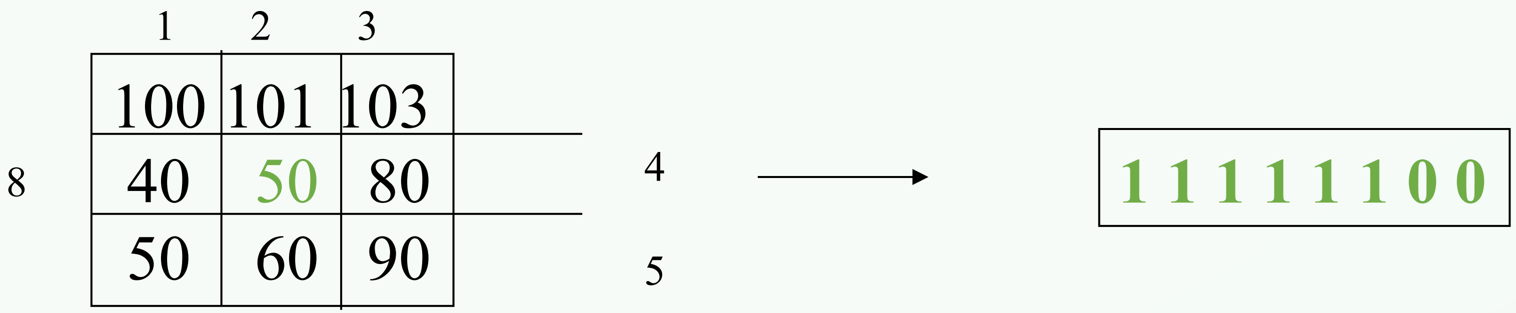
1. Local Binary Pattern

2. Grey Level Co-occurrence

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 bi = 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

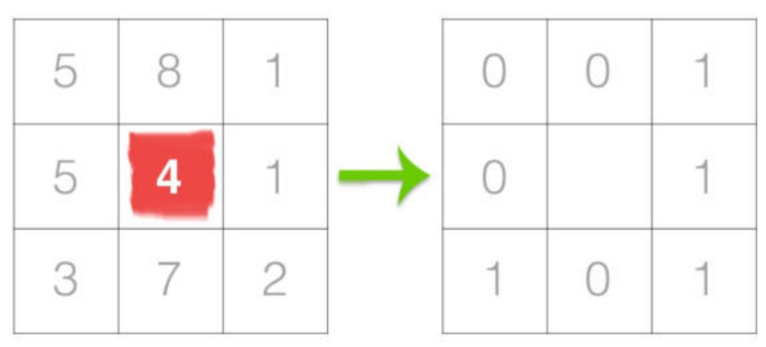


100	101	103
40	50	80
50	60	90

1 1 1 1 1 1 0 0

Examples: LBPs

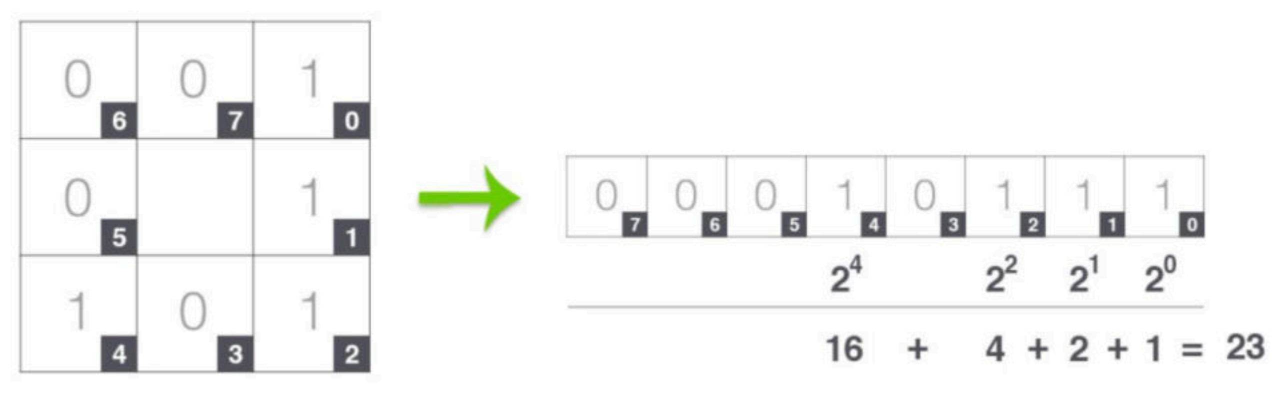
- For each pixel p, create an 8-bit number $b_1\ b_2\ b_3\ b_4\ b_5\ b_6\ b_7\ b_8$



5	8	1
5	**4**	1
3	7	2

→

0	0	1
0		1
1	0	1



0 **6**	0 **7**	1 **0**
0 **5**		1 **1**
1 **4**	0 **3**	1 **2**

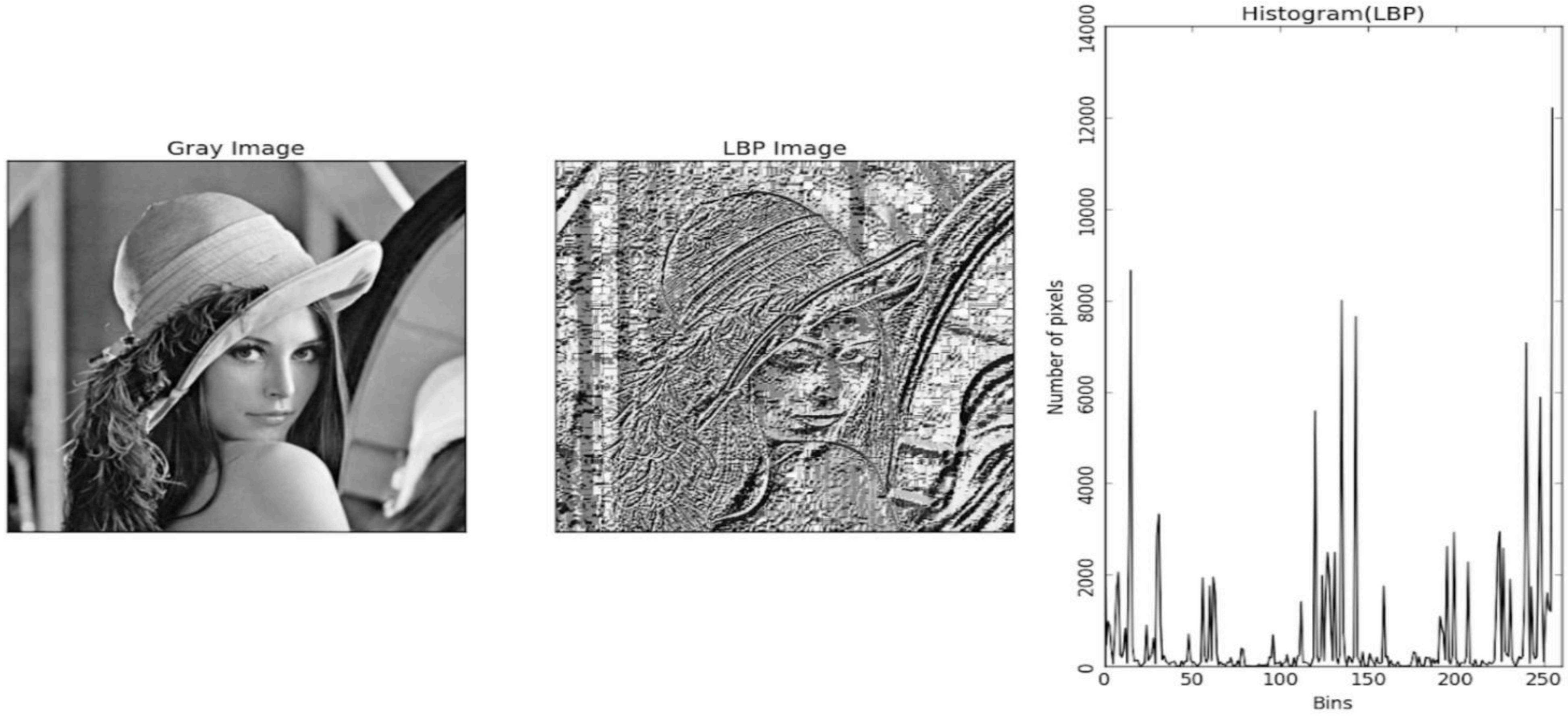
→

0 **7**	0 **6**	0 **5**	1 **4**	0 **3**	1 **2**	1 **1**	1 **0**
			2^4		2^2	2^1	2^0

$$16 + 4 + 2 + 1 = 23$$

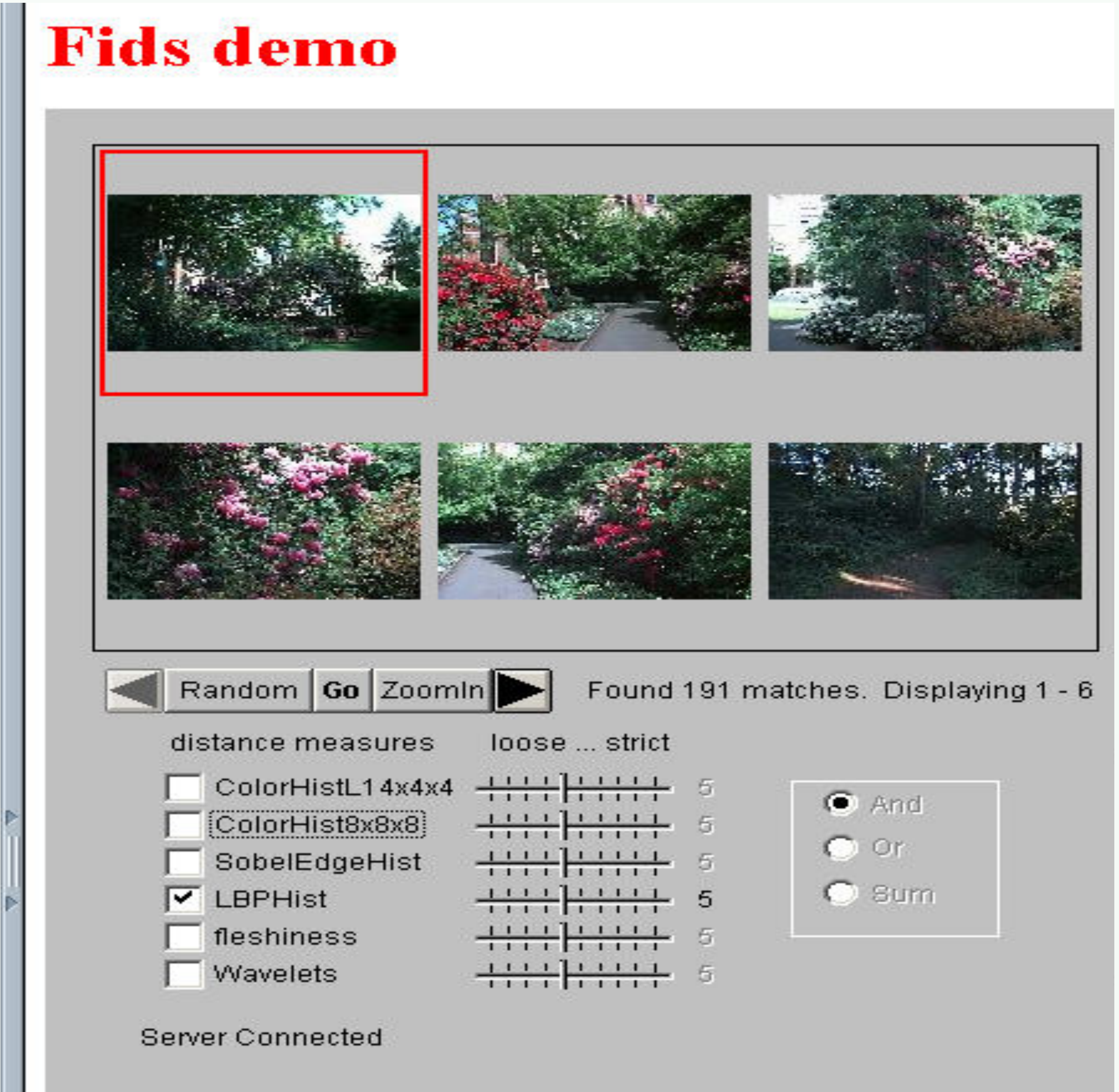
Examples: LBPs

- Image description with local binary pattern



Example: LBPs

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

◀ Random Go ZoomIn ▶ Found 191 matches. Displaying 1 - 6

distance measures loose ... strict

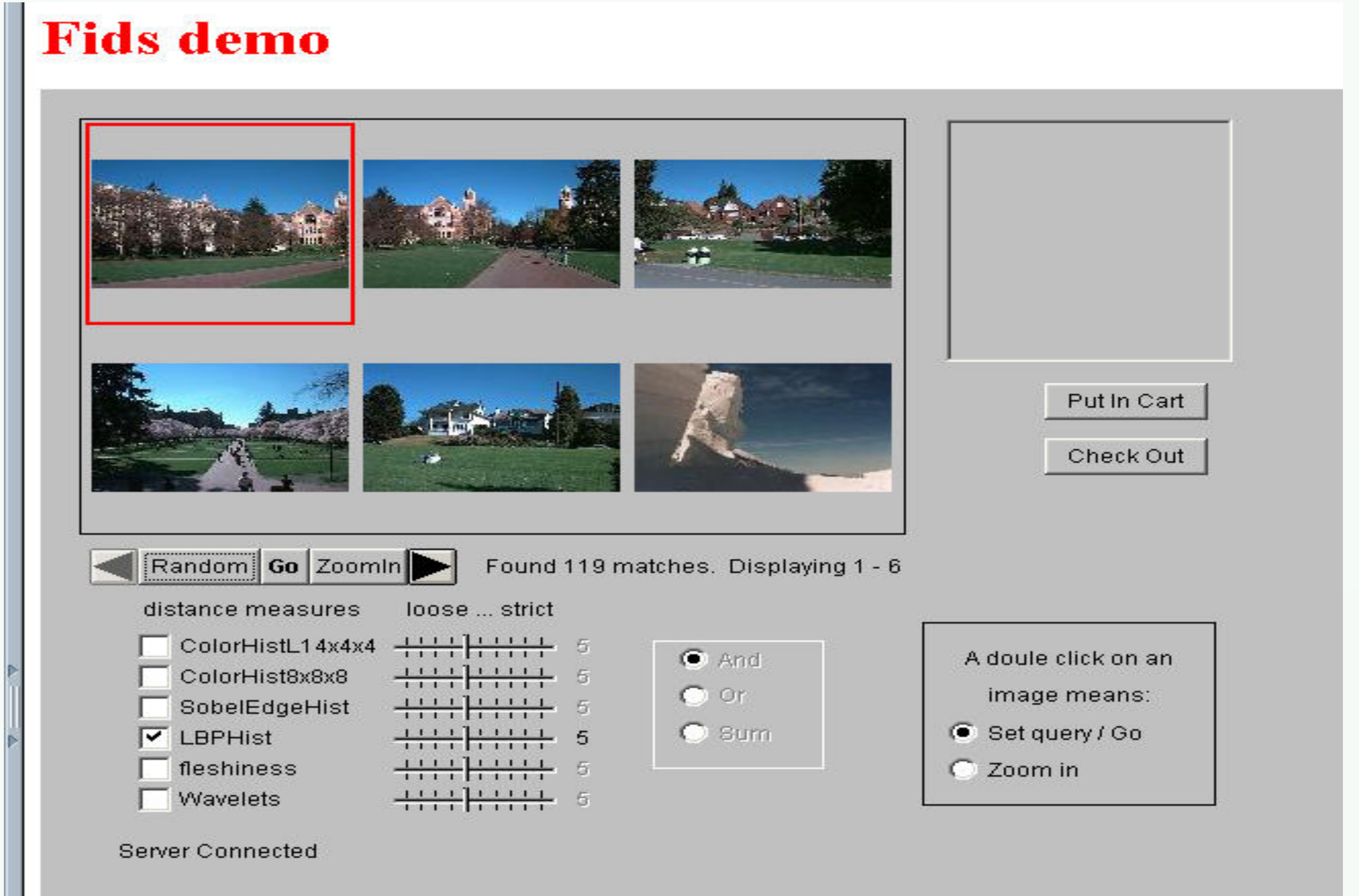
☐ ColorHistL1 4x4x4 5
☐ ColorHist8x8x8 5
☐ SobelEdgeHist 5
☑ LBPHist 5
☐ fleshiness 5
☐ Wavelets 5

● And
○ Or
○ Sum

Server Connected

Example: LBPs

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



Fids demo

Found 119 matches. Displaying 1 - 6

distance measures loose ... strict

☐ ColorHistL1 4x4x4 5
☐ ColorHist8x8x8 5
☐ SobelEdgeHist 5
☑ LBPHist 5
☐ fleshiness 5
☐ Wavelets 5

● And
○ Or
○ Sum

A doule click on an image means:
● Set query / Go
○ Zoom in

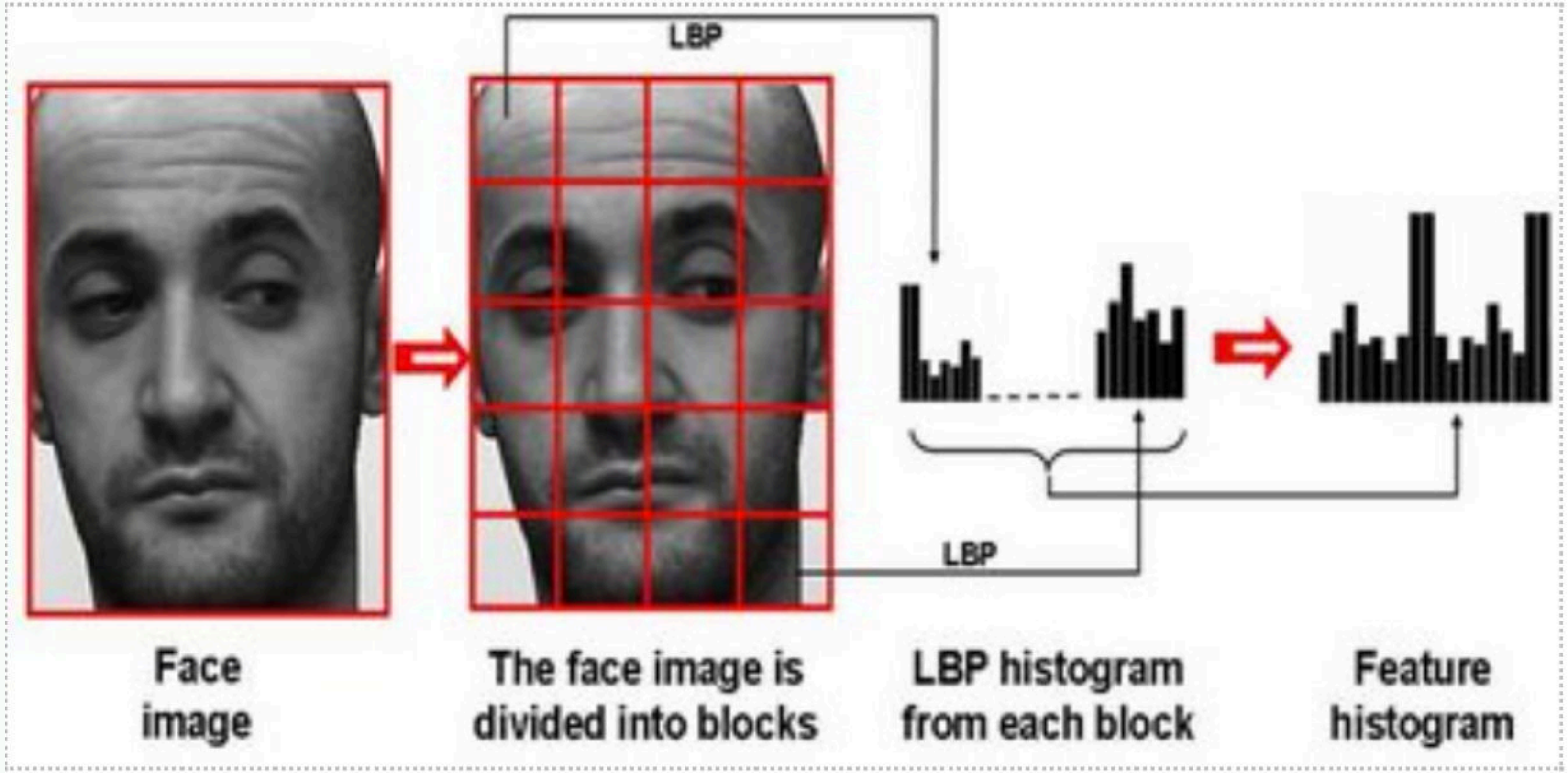
Server Connected

Extension and Applications

- Due to its discriminative power and computational simplicity, it is widely used all over the world both in research and application
- To increase the applicability of LBP, various extensions and modifications have been proposed
-     → Paper reading

Applications: LBPs

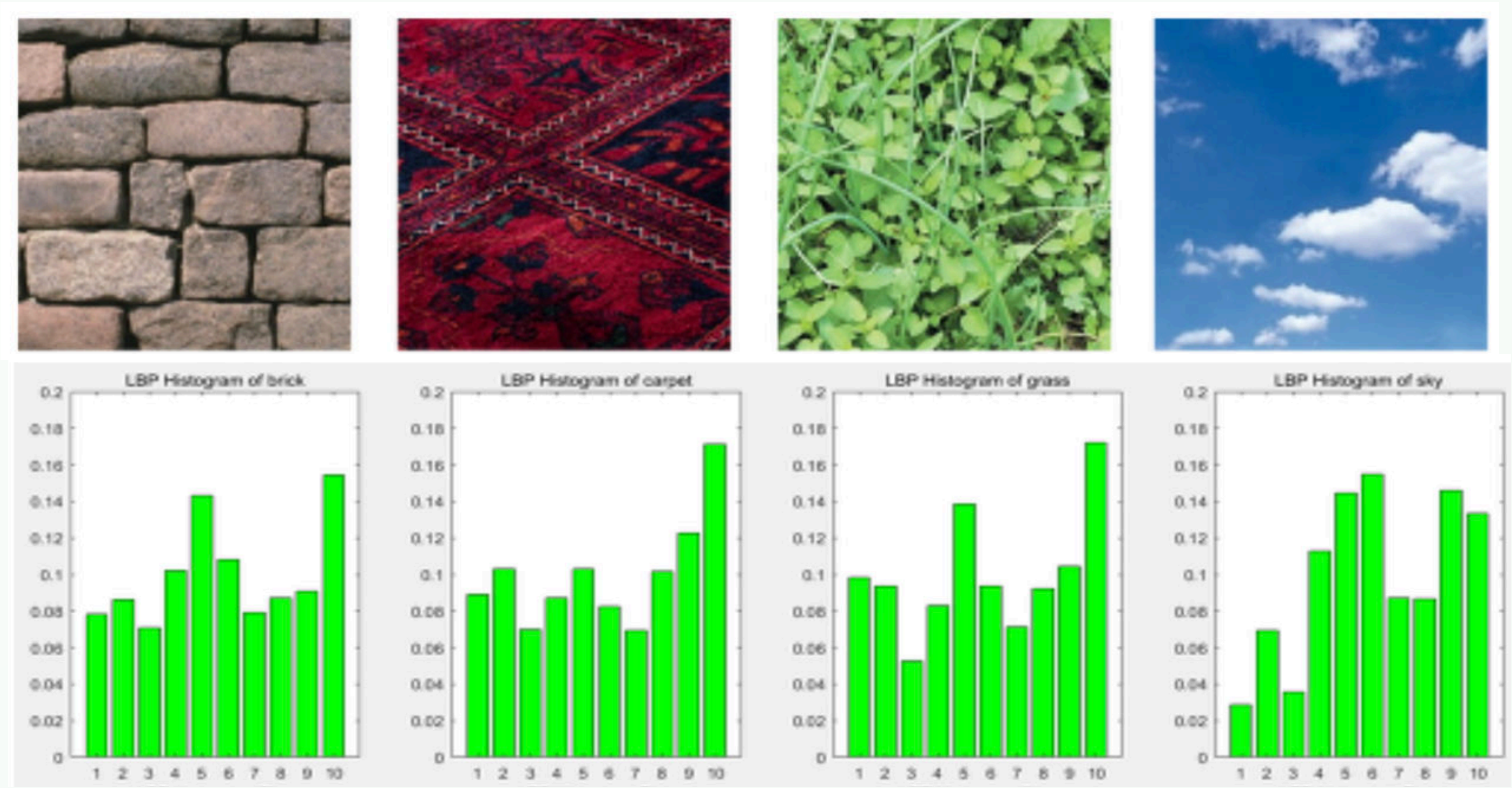
- Face description with local binary patterns *



* T. Ahonen, A. Hadid, and M. Pietikinen, "Face description with local binary patterns: Application to face recognition," PAMI 2006

Applications: LBPs

- Texture classification with uniform & rotation-invariant LBP*

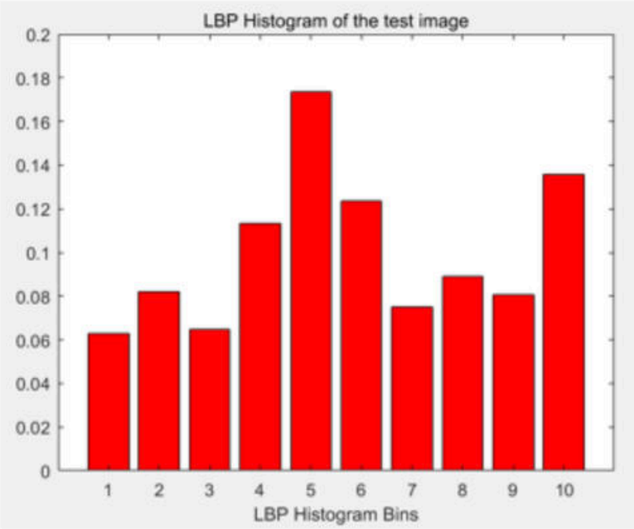


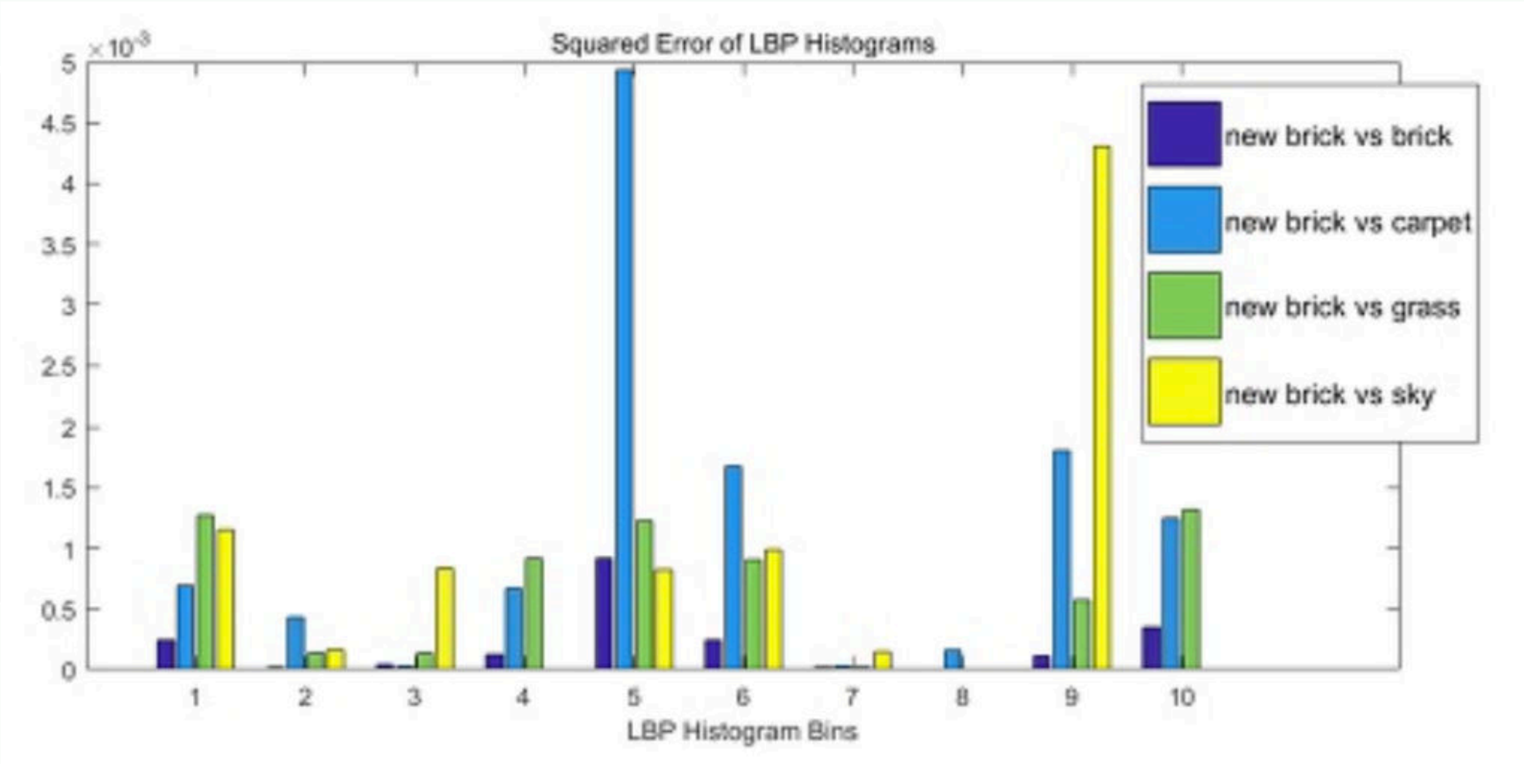
---

* Ojala T, Pietik, Inen M, et al. Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns[M]// Computer Vision - ECCV 2000. Springer Berlin Heidelberg, 2000:404-420.

Applications: LBPs

Test image





Gray Level Co-occurrence

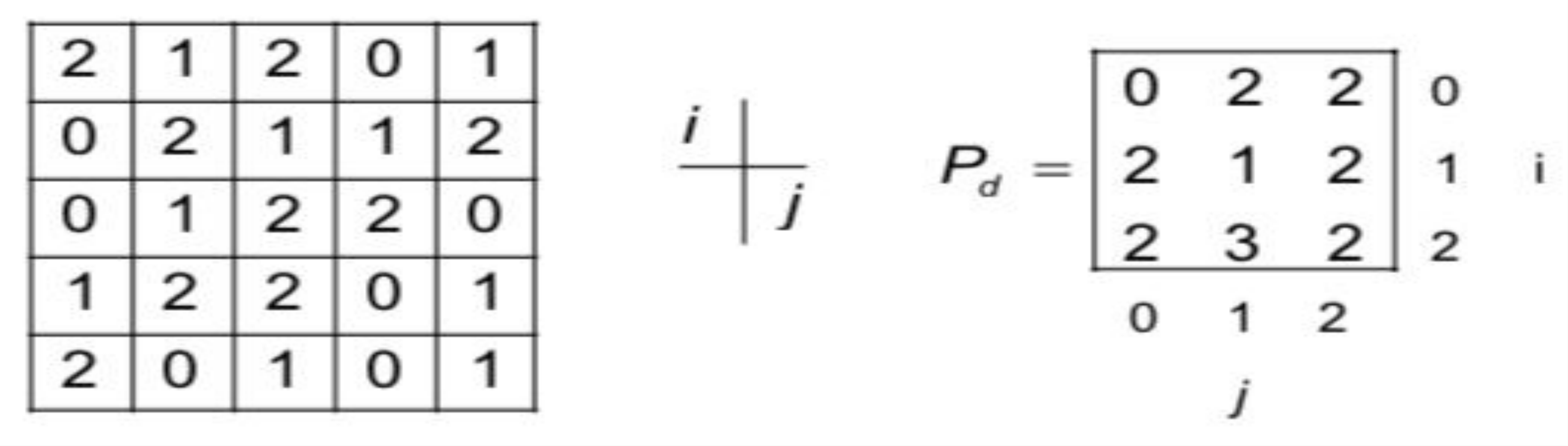
- The statistical measures described so far are easy to calculate, but do not provide any information about the repeating nature of texture.
- A **gray level co-occurrence matrix(GLCM)** contains information about the positions of pixels having similar gray level values.

GLCM

- A co-occurrence matrix is a two-dimensional array, **P**, in which both the rows and the columns represent a set of possible image values
  - A GLCM $\mathbf{P_d[i,j]}$ is defined by first specifying a displacement vector d=(dx,dy) and counting all pairs of pixels separated by d having gray levels i and j.
  - The GLCM is defined by: $\mathbf{P_d[i,j] = n_{ij}}$
    - n_{ij} is the number of occurrences of the pixel values (i,j) lying at distance **d** in the image
    - The co-occurrence matrix $\mathbf{P_d}$ has dimension $n \times n$, where n is the number of gray levels in the image

Example: GLCM

- For example, if d = (1,1)



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

$$P_d = \begin{array}{ccc|cc} 0 & 2 & 2 & 0 & \\ 2 & 1 & 2 & 1 & i \\ 2 & 3 & 2 & 2 & \\ \hline 0 & 1 & 2 & & \\ & j & & & \end{array}$$

  - There are 16 pairs of pixels in the image which satisfy this spatial separation
  - Since there are only three gray levels, **$P_d[i,j]$** is 3×3 matrix

GLCM

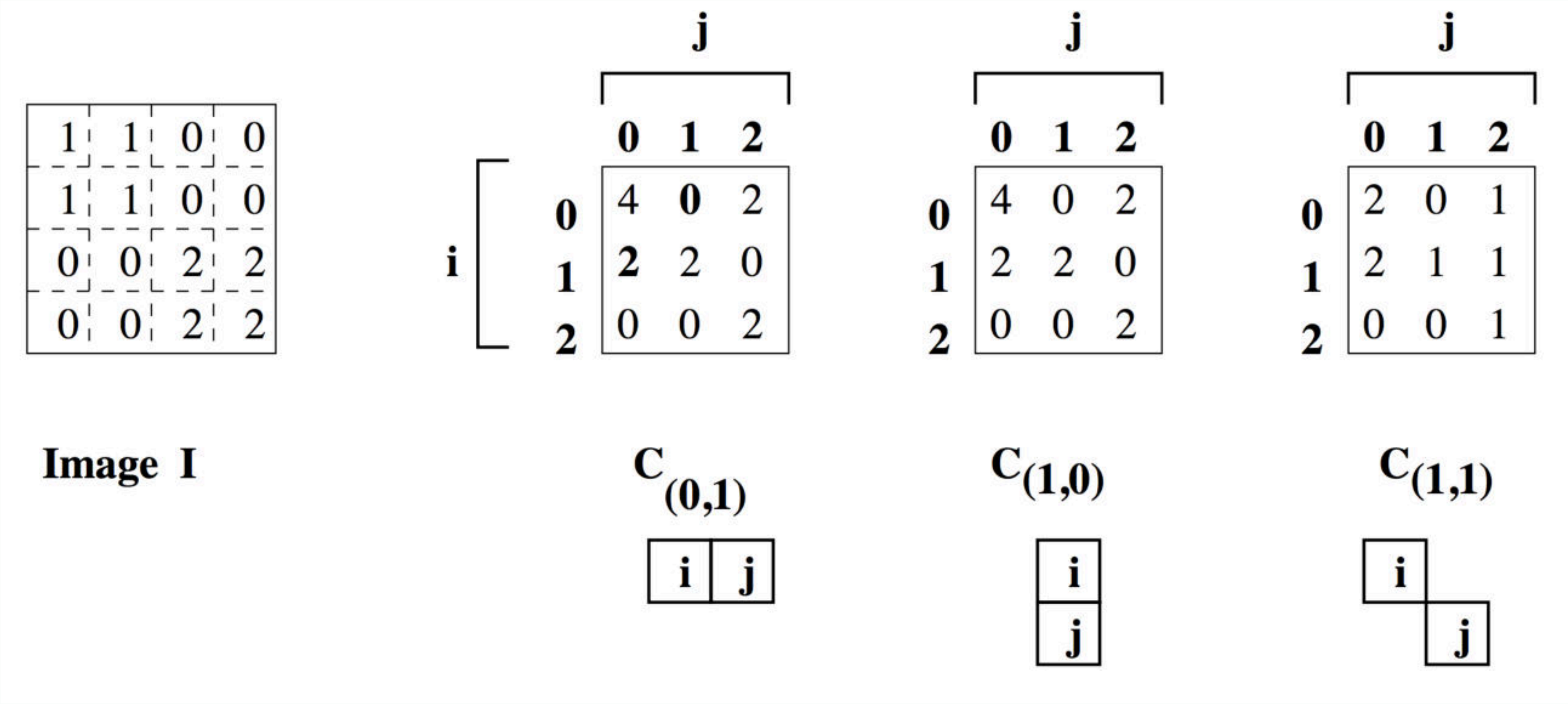


Image I

$$\begin{array}{|c|c|c|c|}\hline 1 & 1 & 0 & 0 \\ \hline 1 & 1 & 0 & 0 \\ \hline 0 & 0 & 2 & 2 \\ \hline 0 & 0 & 2 & 2 \\ \hline\end{array}$$

$C_{(0,1)}$

$$\begin{array}{c|ccc} i \backslash j & 0 & 1 & 2 \\ \hline 0 & 4 & 0 & 2 \\ 1 & 2 & 2 & 0 \\ 2 & 0 & 0 & 2 \end{array}$$

$C_{(1,0)}$

$$\begin{array}{c|ccc} i \backslash j & 0 & 1 & 2 \\ \hline 0 & 4 & 0 & 2 \\ 1 & 2 & 2 & 0 \\ 2 & 0 & 0 & 2 \end{array}$$

$C_{(1,1)}$

$$\begin{array}{c|ccc} i \backslash j & 0 & 1 & 2 \\ \hline 0 & 2 & 0 & 1 \\ 1 & 2 & 1 & 1 \\ 2 & 0 & 0 & 1 \end{array}$$

GLCM

Algorithm:

- Count all pairs of pixels in which the first pixel has a value i, and its matching pair displaced from the first pixel by **d** has a value of j
- This count is entered in the ith row and jth column of the matrix $\mathbf{P_d[i,j]}$
- Note that $\mathbf{P_d[i,j]}$ is not symmetric, since the number of pairs of pixels having gray levels [i,j] does not necessarily equal the number of pixel pairs having gray levels [j,i]

Normalized GLCM

- The elements of $\mathbf{P_d[i,j]}$ can be normalized by dividing each entry by the total number of pixel pairs

- Normalized GLCM, **N[i,j]** is defined by:

$$N[i,j] = \frac{P[i,j]}{\sum_i \sum_j P[i,j]}$$

- It normalizes the co-occurrence values to lie between 0 and 1, and allows the m to be thought of as probabilites

Numeric Features of GLCM

- Gray level co-occurrence matrices capture properties of a texture but they are not directly useful for further analysis, such as the comparison of two textures
- Numeric features are computed from the occurrence matrix that can be used to represent the texture more compactly
  - Maximum probability
  - Moments
  - Contrast
  - Homogeneity
  - Entropy
  - Correlation

Maximum Probability

- This is simply the largest entry in the matrix, and corresponds to the strongest response
  - This could be the maximum in any of the matrices or the maximum overall

$$C_m = \max_{i,j} P_d[i, j]$$

Moments

- The order k element difference moment can be defined as:

$$MOM_k = \sum_i \sum_j (i-j)^k P_d[i,j]$$

- This descriptor has small values in cases where the largest elements in P are along the principal diagonal. The opposite effect can be achieved using the inverse moment

$$MOM_k = \sum_i \sum_j \frac{P_d[i,j]}{(i-j)^k}, \qquad i \neq j$$

Contrast

- Contrast is a measure of the local variations present in an image

$$C(k,n) = \sum_i \sum_j (i-j)^k P_d[i,j]^n$$

  - If there is a large amount of variation in an image the P[i,j]’s will be concentrated away from the main diagonal and contrast will be high
  - Typically, k=2 and n=1

Homogeneity

- A homogeneous image will result in a co-occurrence matrix with a combination of high and low P[i,j]'s

$$C_h = \sum_i \sum_j \frac{P_d[i,j]}{1 + |i - j|}$$

  - Where the range of gray levels is small, the P[i,j] will tend to be clustered around the main diagonal
  - A heterogeneous image will result in an even spread of P[i,j]'s

Entropy

- Entropy is a measure of information content
- It measures the randomness of intensity distribution

$$C_e = -\sum_i \sum_j P_d[i,j] \ln P_d[i,j]$$

- Entropy is highest when all entries in P[i,j] are of similar magnitude, and small when the entries in P[i,j] are unequal

Correlation

- Correlation is a measure of image linearity

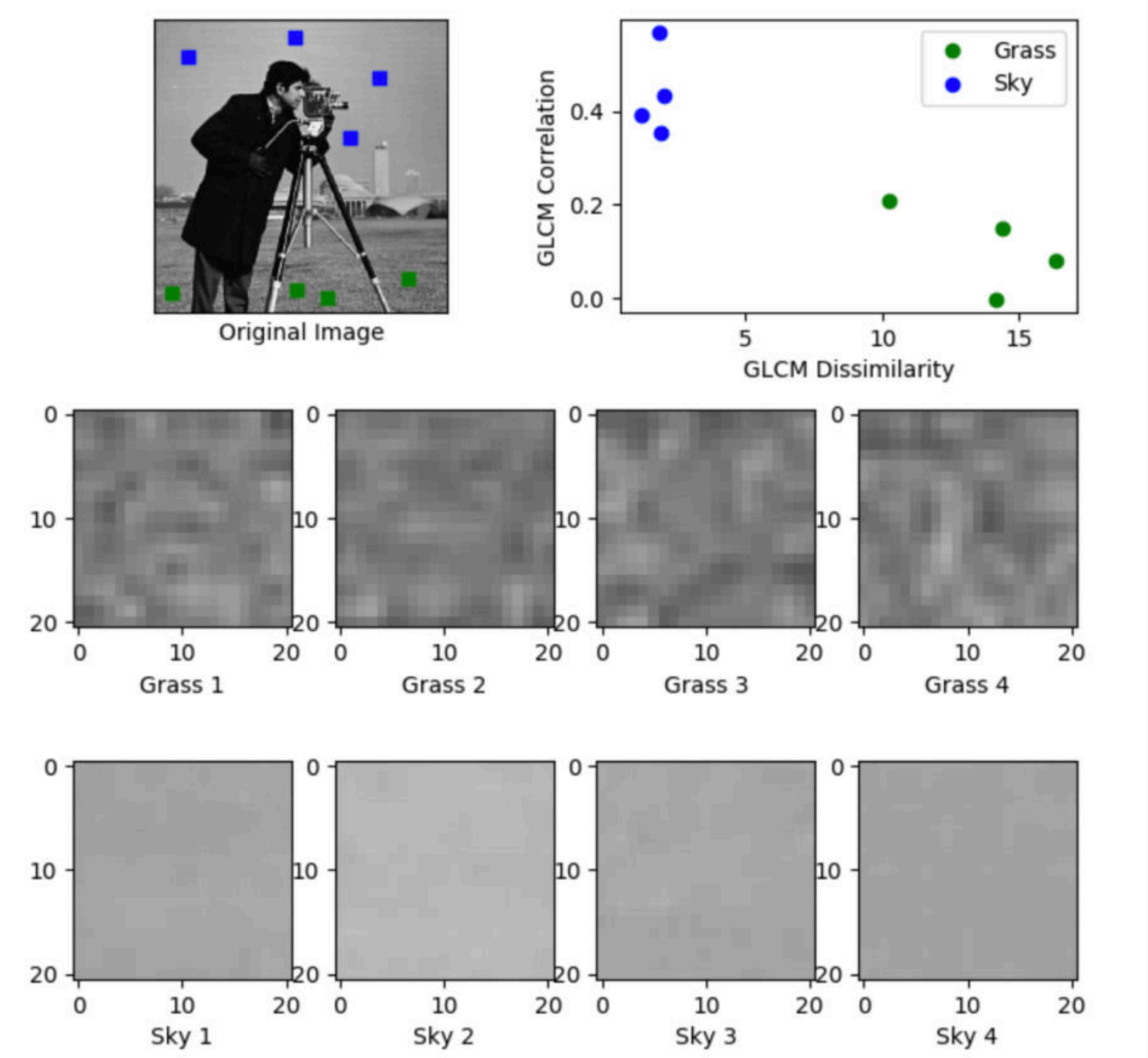
$$C_e = \frac{\sum_i \sum_j ij P_d[i,j] - \mu_i \mu_j}{\sigma_i \sigma_j}$$

$$\mu_i = \sum i P_d[i,j], \qquad \sigma_i^2 = \sum i^2 P_d[i,j] - \mu_i^2$$

- Correlation will be high if an image contains a considerable amount of linear structure

Examples: GLCM

- Texture classification with GLCM numeric feature



Problems with GLCM

- One problem with deriving texture measures from co-occurrence matrices is how to choose the displacement vector **d**
  - The choice of the displacement vector is an important parameter in the definition of the GLCM
  - Occasionally the GLCM is computed from several values of **d** and the one which maximizes a statistical measure computed from P[i,j] is used
  - Zucker and Terzopoulos used a χ^2 measure to select the values of **d** that have the most structure, i.e., to maximize the value

$$\chi^2(d) = \sum_i \sum_j \frac{P_d^2[i,j]}{P_d[i]P_d[j]} - 1$$

Windowing

- Algorithms for texture analysis are applied to an image in a series of windows of size *w*, each centered on a pixel (i,j)
  - The value of the resulting statistical measure are assigned to the position (i,j) in the new pixel

Edges and Texture

Edges and Texture

- It should be possible to locate the edges that result from the intensity transitions along the boundary of the texture
  - Since a texture will have large numbers of texels, there should be a property of the edge pixels that can be used to characterize the texture

- Compute the co-occurrence matrix of an edge-enhanced image

Edges and Texture

- **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 for a region R

Fedgeness = |{ p | gradient_magnitude(p) ≥ threshold}| / N

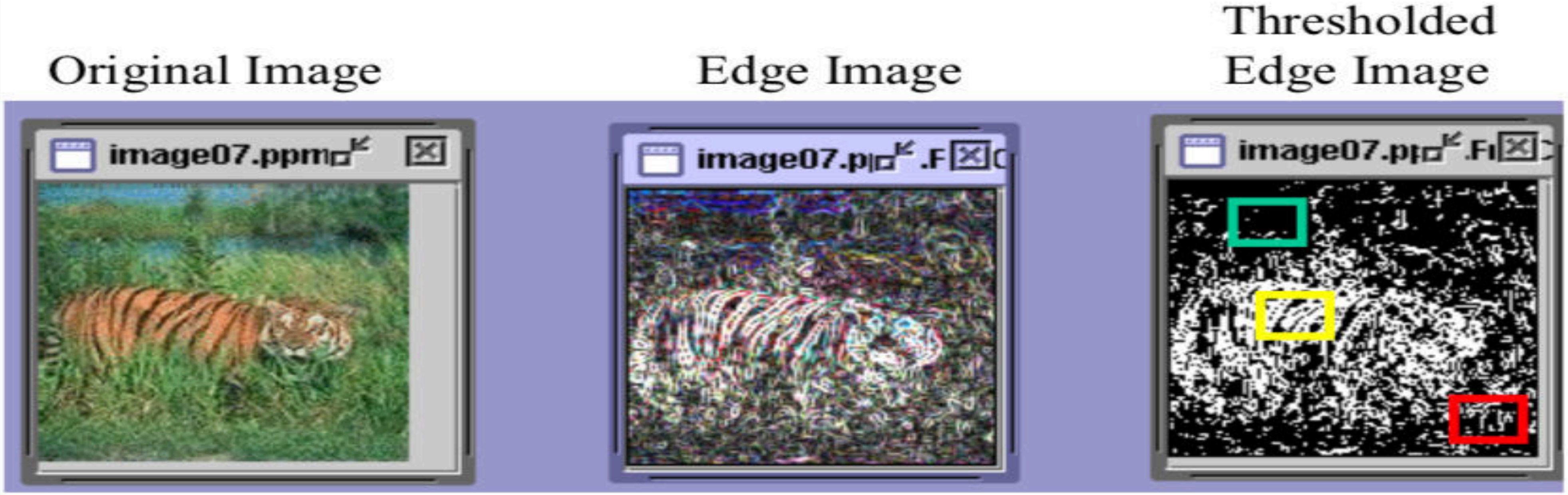
- N is the size of the unit area

2. Histograms of edge magnitude and direction for a region R

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

- These are the normalized histograms of gradient magnitudes and gradient directions, respectively

Example



Original Image

Edge Image

Thresholded Edge Image

Different F_{edgeness} for different regions

Energy and Texture

- One approach to generate texture features is to use local kernels to detect various types of texture

- Laws[1)] developed a texture-energy approach that measures the amount of variation within a fixed size window

- 1) Laws, K. I. “Rapid texture identification”. in SPIE Image Processing for Missile Guidance, pp. 370-380, 1980.

Law’s Texture Energy

- 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 Mask

- A set of convolution mask are used to compute texture energy
- The mask are computed from the following basic mask
  - L5 (Gaussian) gives a center-weighted local average
  - E5 (gradient) responds to row or col step edges
  - S5 (LoG) detectss spots
  - R5 (Gabor) detects ripples
  - W5(wave) detects waves

$$L5 = [1 \quad 4 \quad 6 \quad 4 \quad 1]$$

$$E5 = [-1 \quad -2 \quad 0 \quad 2 \quad 1]$$

$$S5 = [-1 \quad 0 \quad 2 \quad 0 \quad -1]$$

$$R5 = [1 \quad -4 \quad 6 \quad -4 \quad 1]$$

$$W5 = [-1 \quad 2 \quad 0 \quad -2 \quad -1]$$

Law’s Texture Mask (2D)

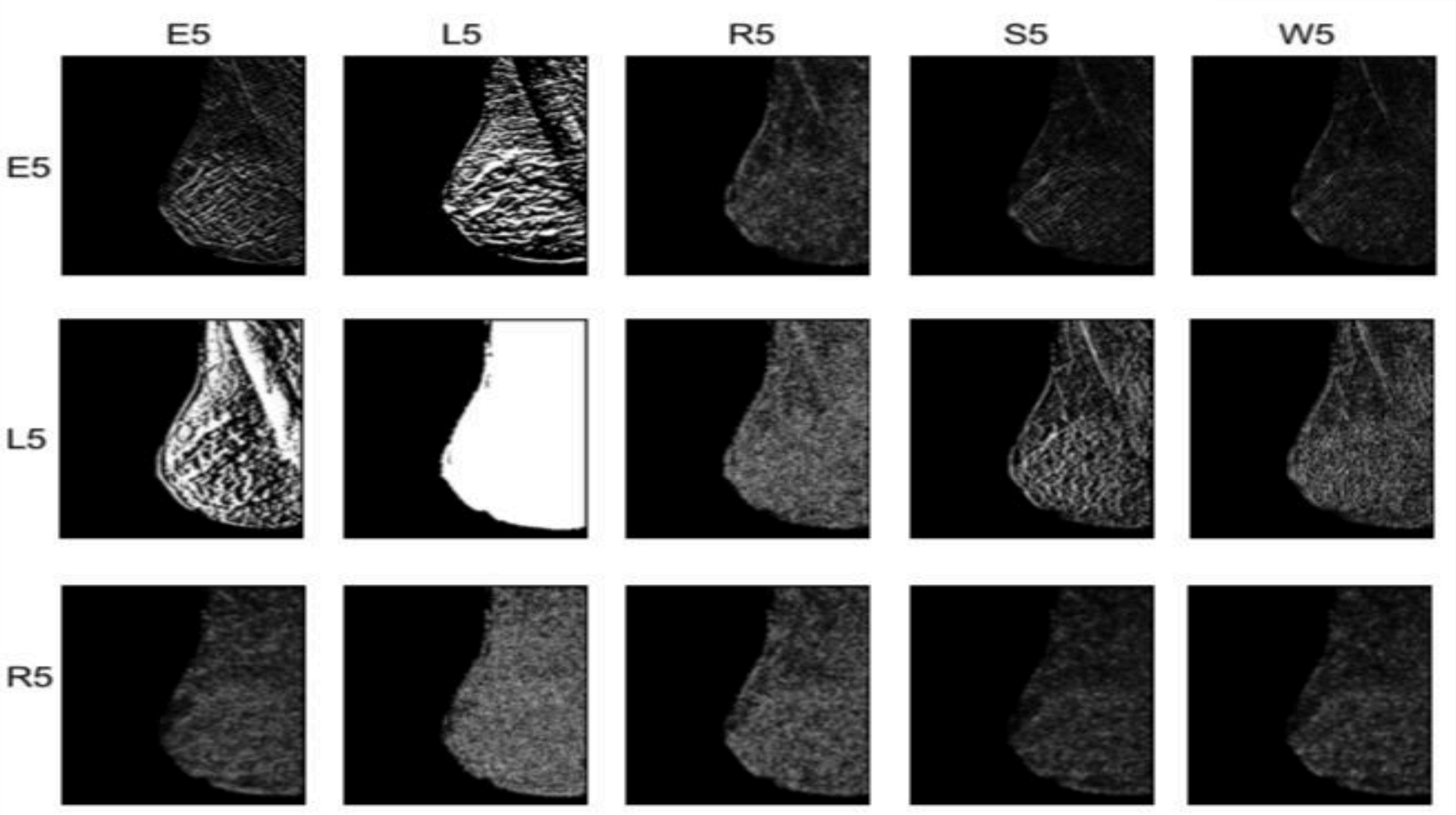
- The 2D convolution mask are obtained by computing the outer product of a pair of vectors
- For example, **E5L5** is computed as the product of **E5** and **L5** as follows

$$\begin{bmatrix}-1\\-2\\0\\2\\1\end{bmatrix}\times\begin{bmatrix}1 & 4 & 6 & 4 & 1\end{bmatrix}=\begin{bmatrix}-1 & -4 & -6 & -4 & -1\\-2 & -8 & -12 & -8 & -2\\0 & 0 & 0 & 0 & 0\\2 & 8 & 12 & 8 & 2\\1 & 4 & 6 & 4 & 1\end{bmatrix}$$

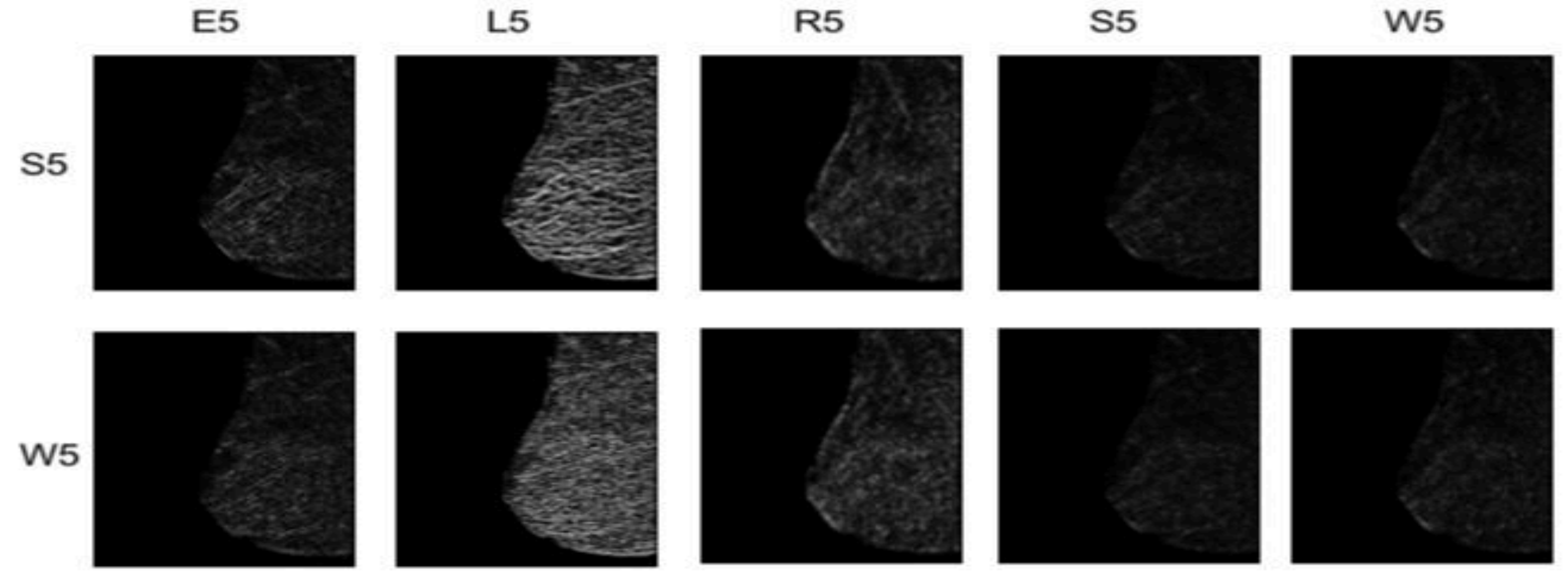
- This resu .5L5 is not

Example

Artificial Inteligence
& Computer Vision
Laboratory

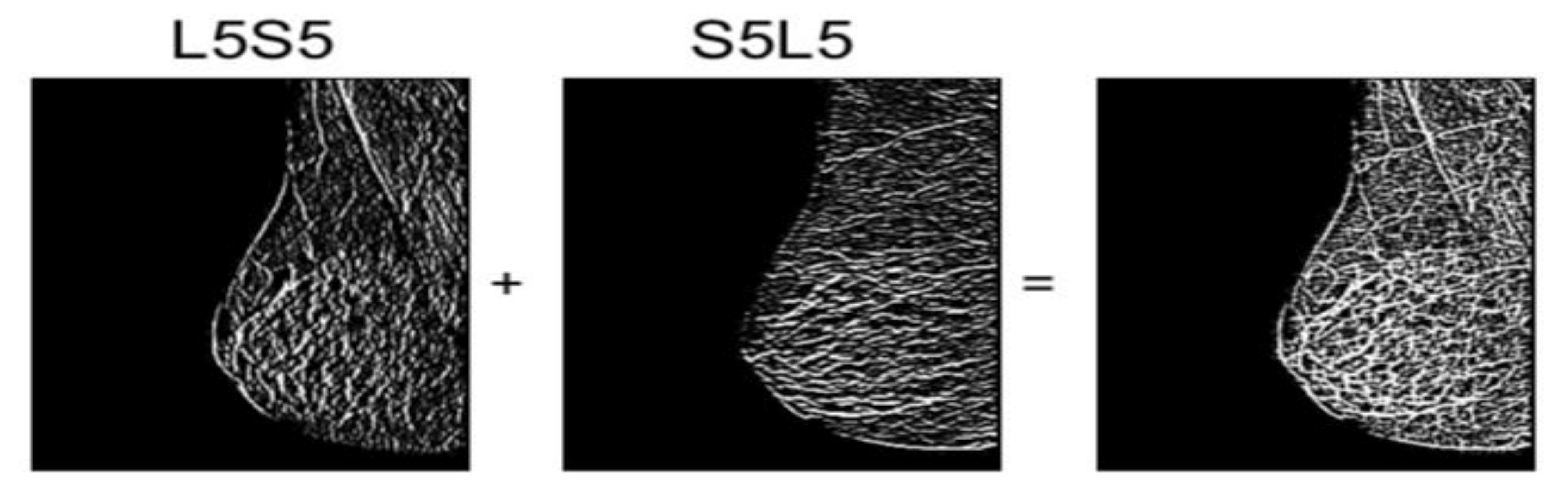


Example



Law's Texture Mask (2D)

- Bias from the "directionality" of textures can be removed by combining symmetric pairs of features, making them rotationally invariant
  - For example, S5L5 (H) + L5S5 (V) = L5S5R



Law’s Texture Energy

- After the convolution with the specified mask, the texture energy measure (TEM) is computed by summing the absolute values in a local neighborhood:

$$L_e = \sum_{i=1}^{m} \sum_{j=1}^{n} |C(i,j)|$$

- If *n* masks are applied, the result is an n-dimensional feature vector at each pixel of the image being analyzed

Law’s Texture Energy

- **Algorithm:**

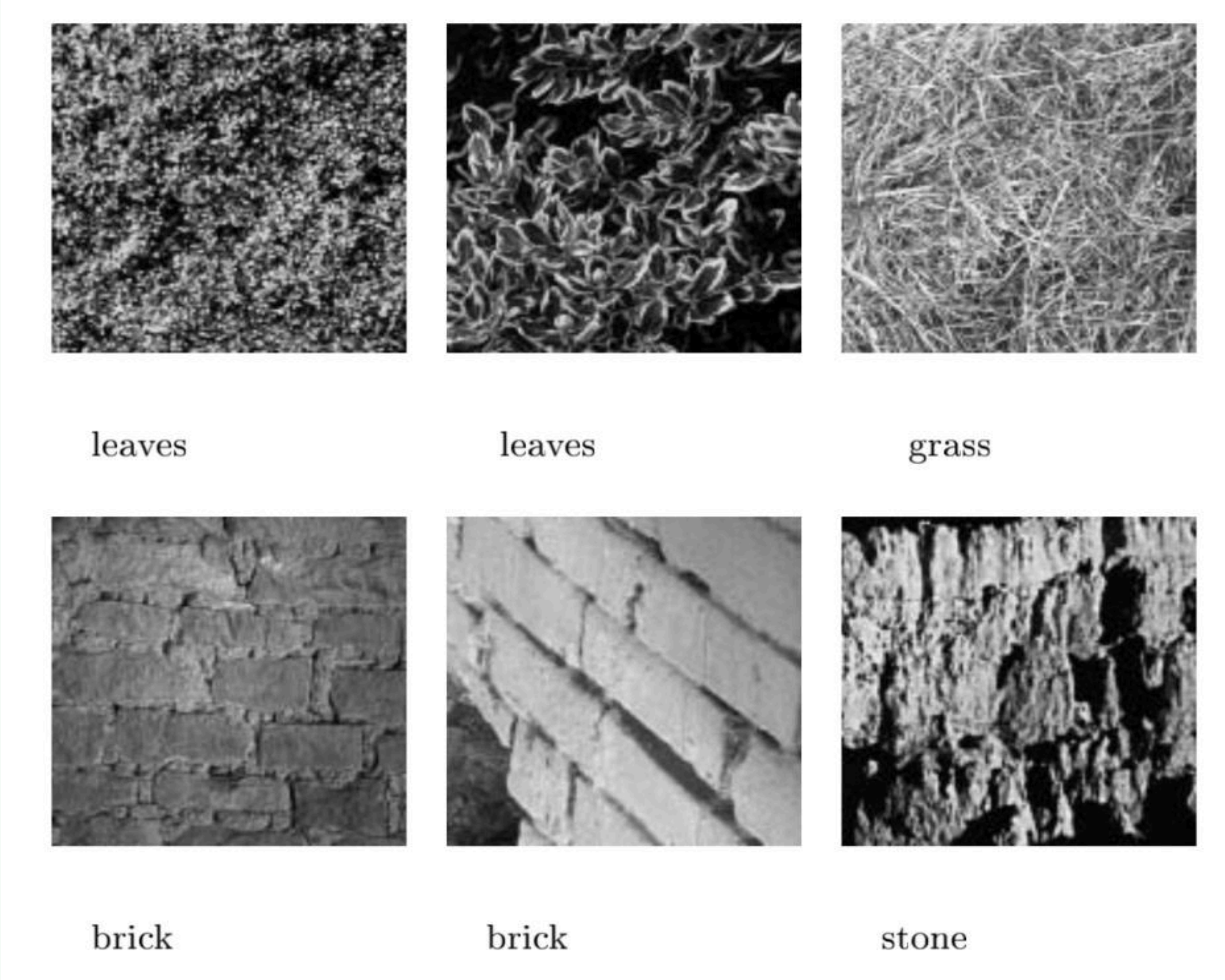
1. Apply convolution masks
2. Calculate the texture energy measure (TEM) at each pixel. This is achieved by summing the absolute values in a local neighborhood
3. Normalize features – use L5L5 to normalize the TEM image

Using Law’s energy for segmentation

- Subtract mean neighborhood intensity from pixel (to reduce illumination effects)
- Filter the neighborhood with 16 masks
- Compute energy at each pixel by summing absolute value of filter output across neighborhood around pixel
- Define 9 features as follows (replace each pair with average)
  - L5E5 / E5L5
  - L5R5 / R5L5
  - E5S5 / S5E5
  - S5S5
  - R5R5
  - L5S5 / S5L5
  - E5R5 / R5E5
  - S5R5 / S5R5
  - E5E5

Example: Law' Energy

- Natural textures (from MIT Media Lab VisTex Database)



Example: Law' Energy

- Natural textures (from MIT Media Lab VisTex Database)

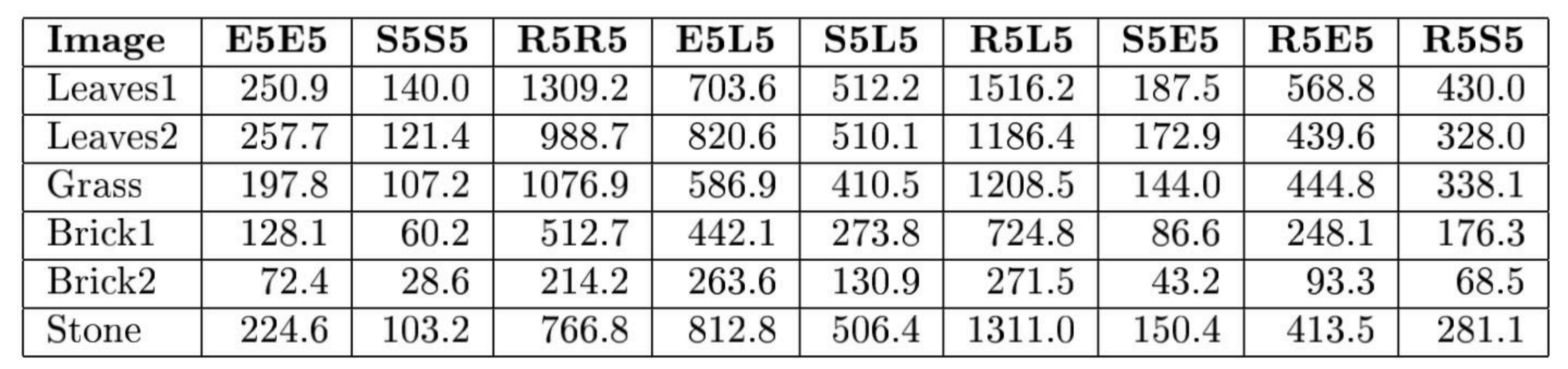
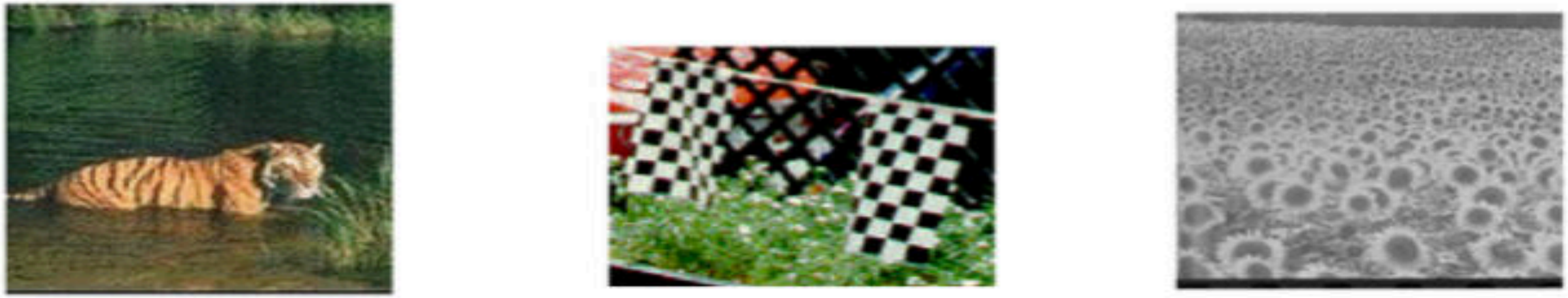


Image	E5E5	S5S5	R5R5	E5L5	S5L5	R5L5	S5E5	R5E5	R5S5
Leaves1	250.9	140.0	1309.2	703.6	512.2	1516.2	187.5	568.8	430.0
Leaves2	257.7	121.4	988.7	820.6	510.1	1186.4	172.9	439.6	328.0
Grass	197.8	107.2	1076.9	586.9	410.5	1208.5	144.0	444.8	338.1
Brick1	128.1	60.2	512.7	442.1	273.8	724.8	86.6	248.1	176.3
Brick2	72.4	28.6	214.2	263.6	130.9	271.5	43.2	93.3	68.5
Stone	224.6	103.2	766.8	812.8	506.4	1311.0	150.4	413.5	281.1

Using Law's energy for segmentation



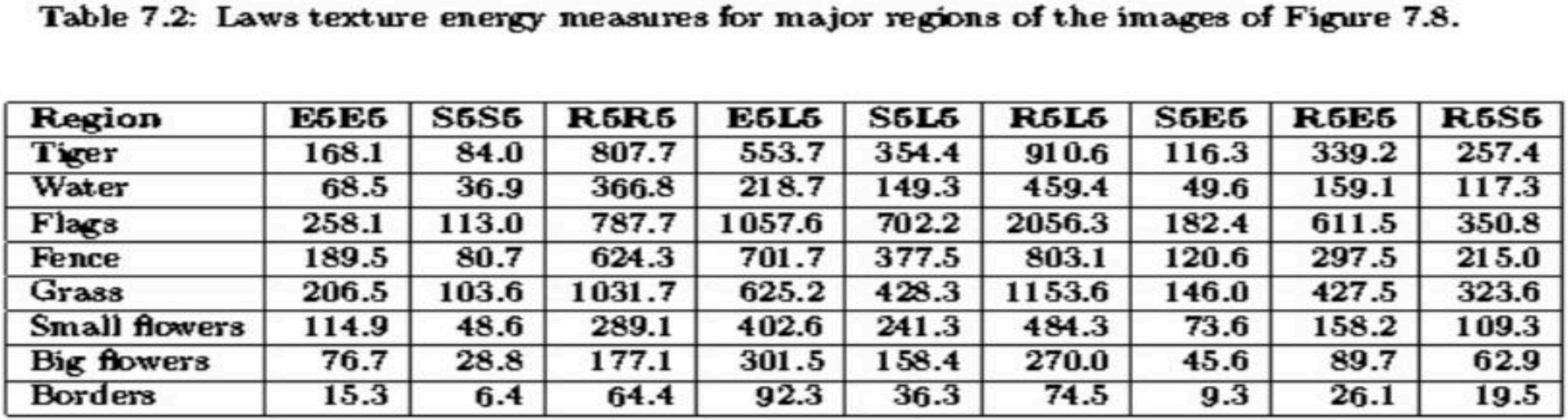


Table 7.2: Laws texture energy measures for major regions of the images of Figure 7.8.

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

Using Law's energy for segmentation

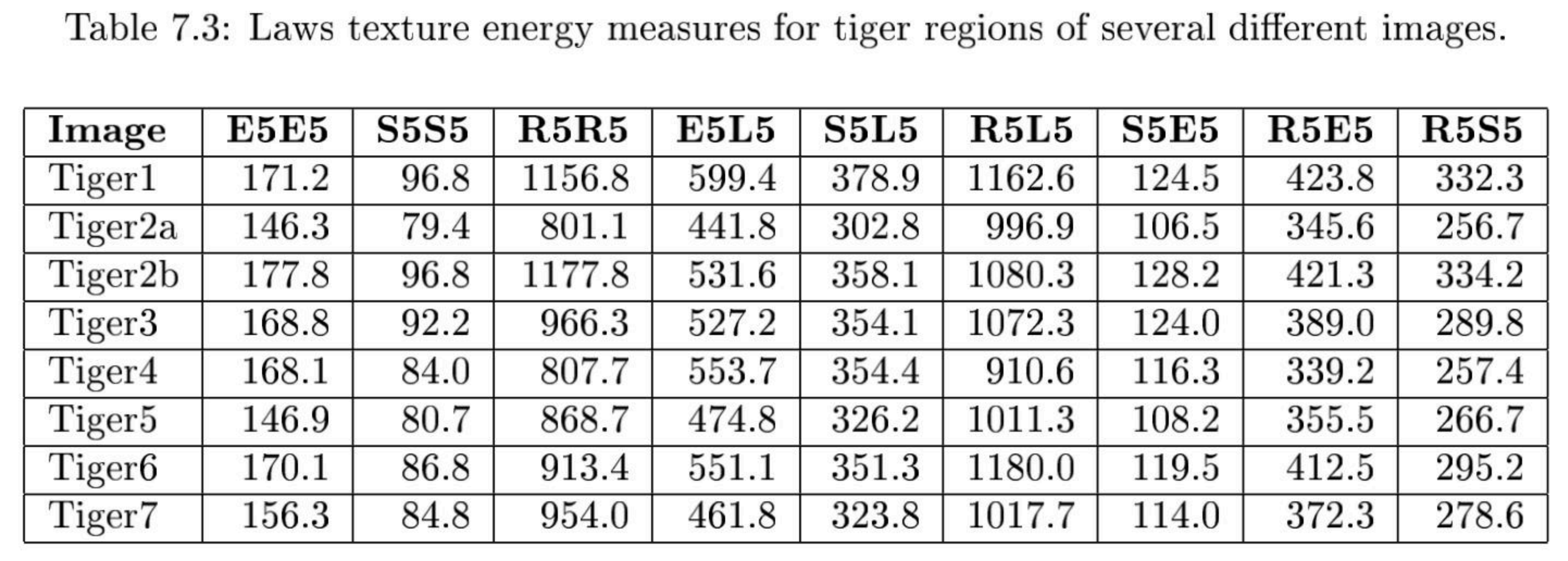
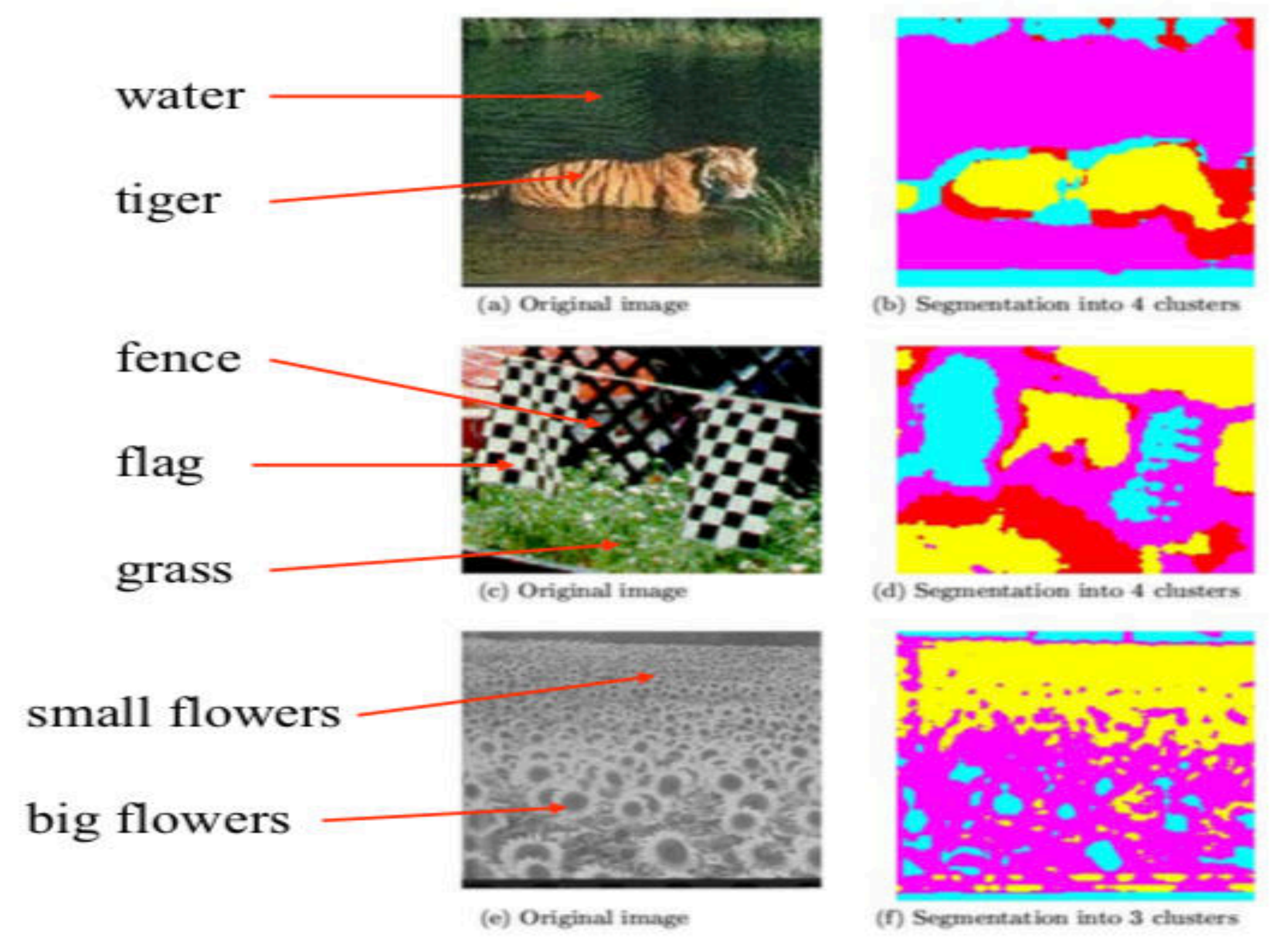


Table 7.3: Laws texture energy measures for tiger regions of several different images.

Image	**E5E5**	**S5S5**	**R5R5**	**E5L5**	**S5L5**	**R5L5**	**S5E5**	**R5E5**	**R5S5**
Tiger1	171.2	96.8	1156.8	599.4	378.9	1162.6	124.5	423.8	332.3
Tiger2a	146.3	79.4	801.1	441.8	302.8	996.9	106.5	345.6	256.7
Tiger2b	177.8	96.8	1177.8	531.6	358.1	1080.3	128.2	421.3	334.2
Tiger3	168.8	92.2	966.3	527.2	354.1	1072.3	124.0	389.0	289.8
Tiger4	168.1	84.0	807.7	553.7	354.4	910.6	116.3	339.2	257.4
Tiger5	146.9	80.7	868.7	474.8	326.2	1011.3	108.2	355.5	266.7
Tiger6	170.1	86.8	913.4	551.1	351.3	1180.0	119.5	412.5	295.2
Tiger7	156.3	84.8	954.0	461.8	323.8	1017.7	114.0	372.3	278.6

Using Law’s energy for segmentation



(a) Original image (b) Segmentation into 4 clusters

(c) Original image (d) Segmentation into 4 clusters

(e) Original image (f) Segmentation into 3 clusters

Autocorrelation for texture

- Autocorrelation function computes the dot product (energy) of original image with shifted image for different shifts

$$\rho(dr,dc)=\frac{\sum_i\sum_j I[i,j]I[i+dr,j+dc]}{\sum_i\sum_j I^2[i,j]}=\frac{I[i,j]\circ I_d[i,j]}{I[i,j]\circ I[i,j]}$$

- It can detect repetitive patterns of texels
- Also it can captures fineness/coarseness of the texture

Interpreting Autocorrelation

- Regular textures : function will have peaks and valleys
- Random textures: only peak at [0,0] and breadth of peak gives the size of the texture
- Coarse texture: function drops off slowly
- Fine texture : function drops off rapidly

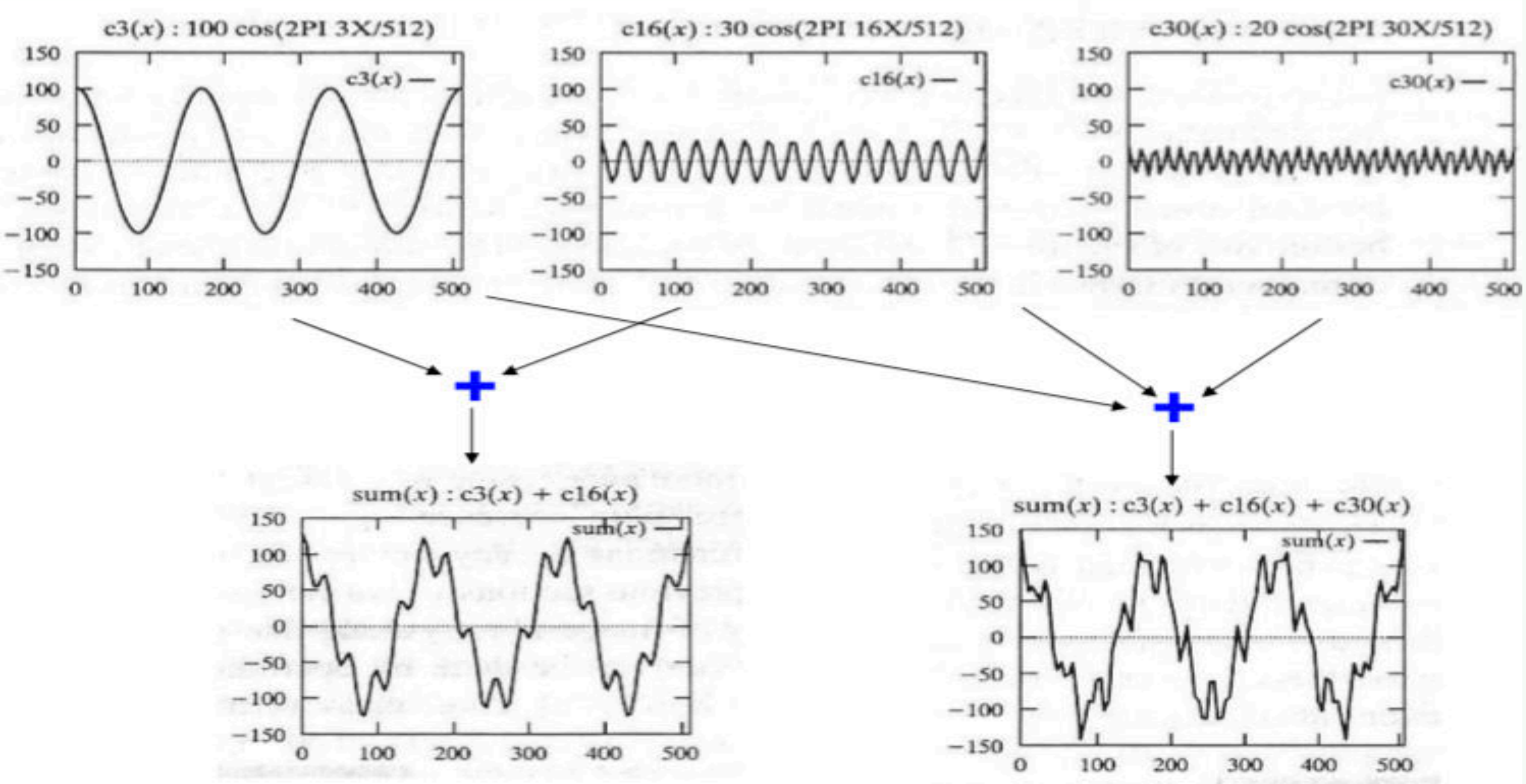
- Can drop differently for row and column

Relationship to Fourier Analysis

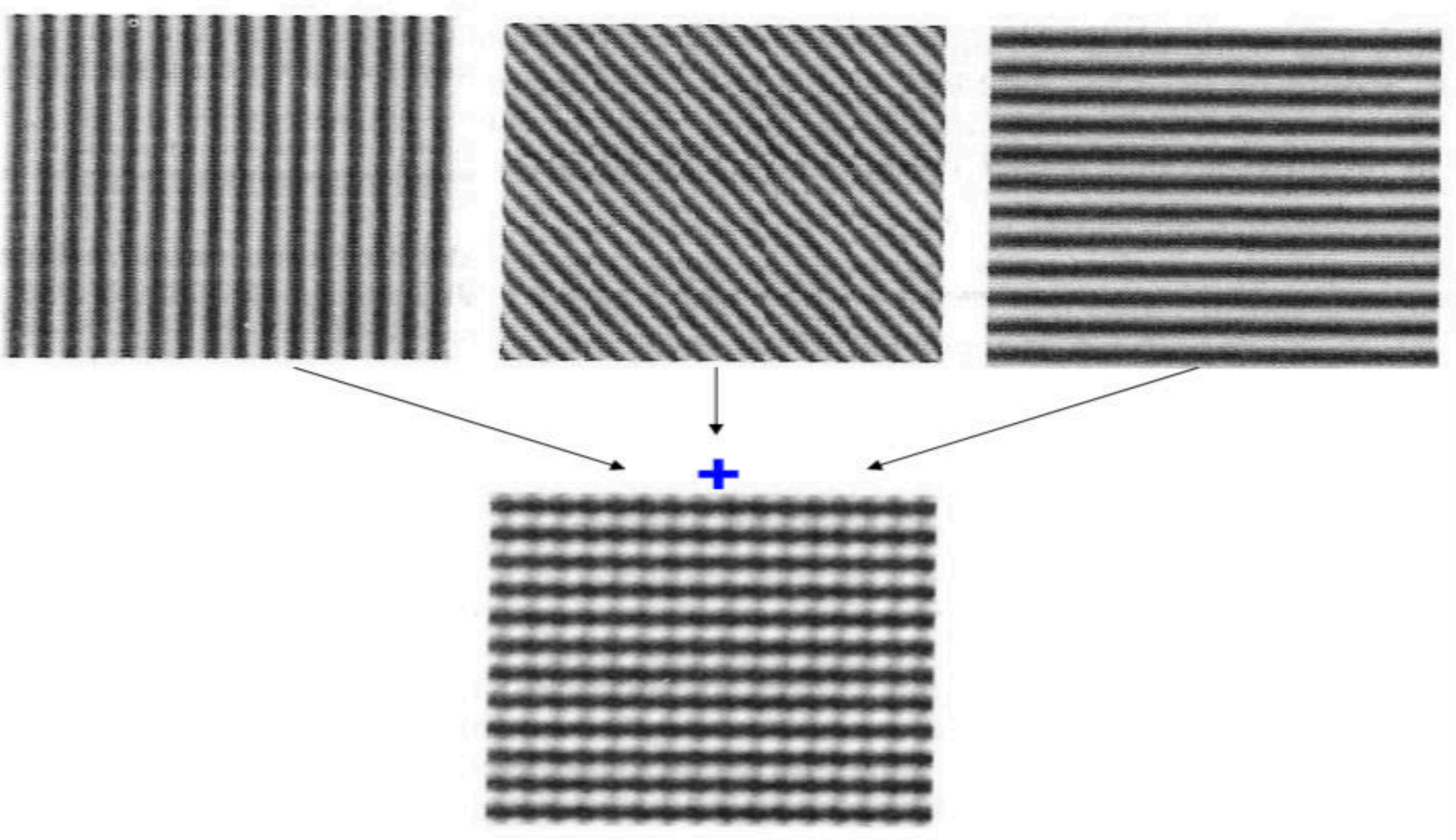
- The power spectrum of a signal is the Fourier transform of the autocorrelation function
- What is the Fourier transform?
  - Representing signals with sine/cosine waves

1D Example

Artificial Inteligence
& Computer Vision
Laboratory

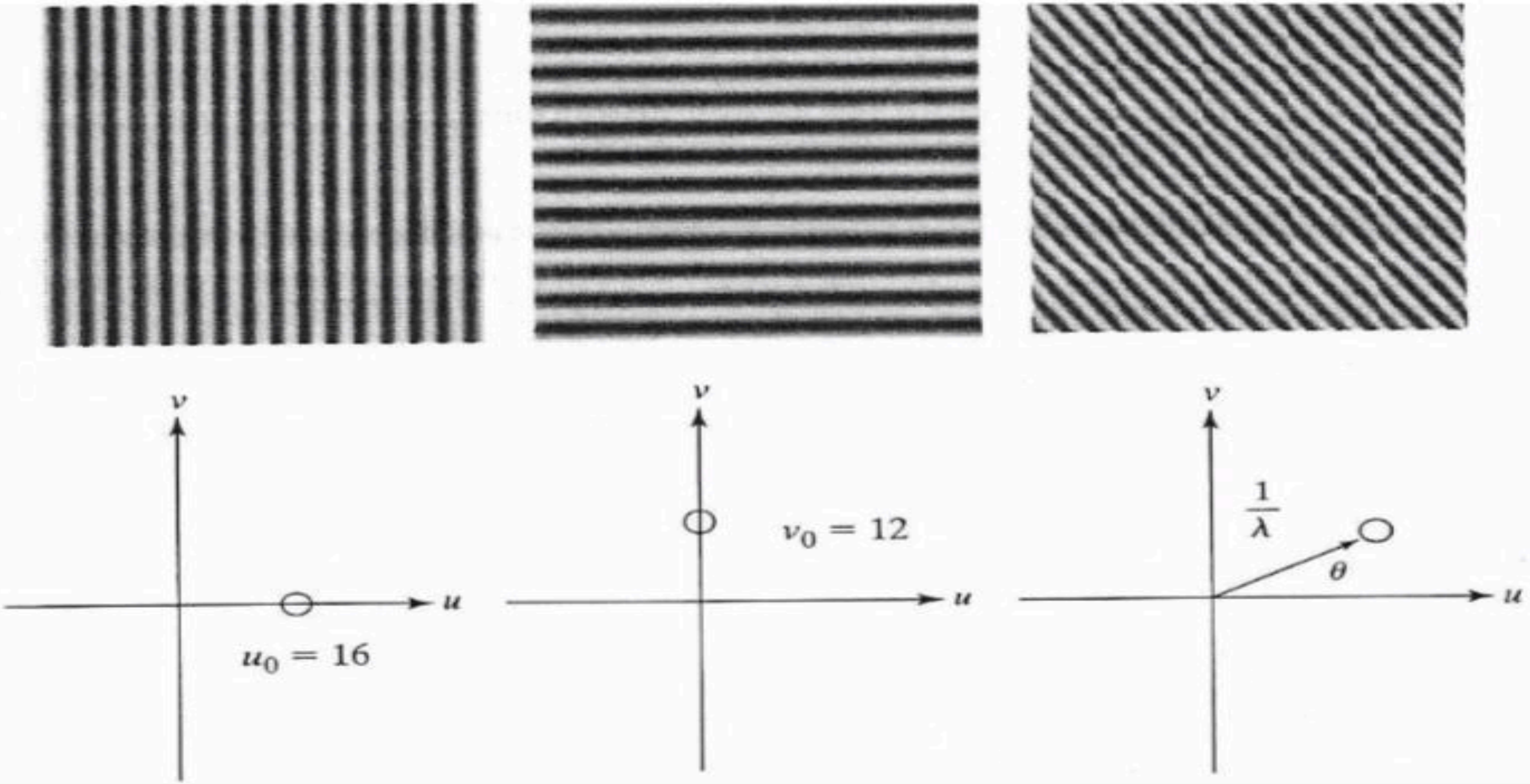


2D Example



Power Spectrum

$$P(u, v) \equiv (Real(F(u, v))^2 + Imaginary(F(u, v))^2)$$

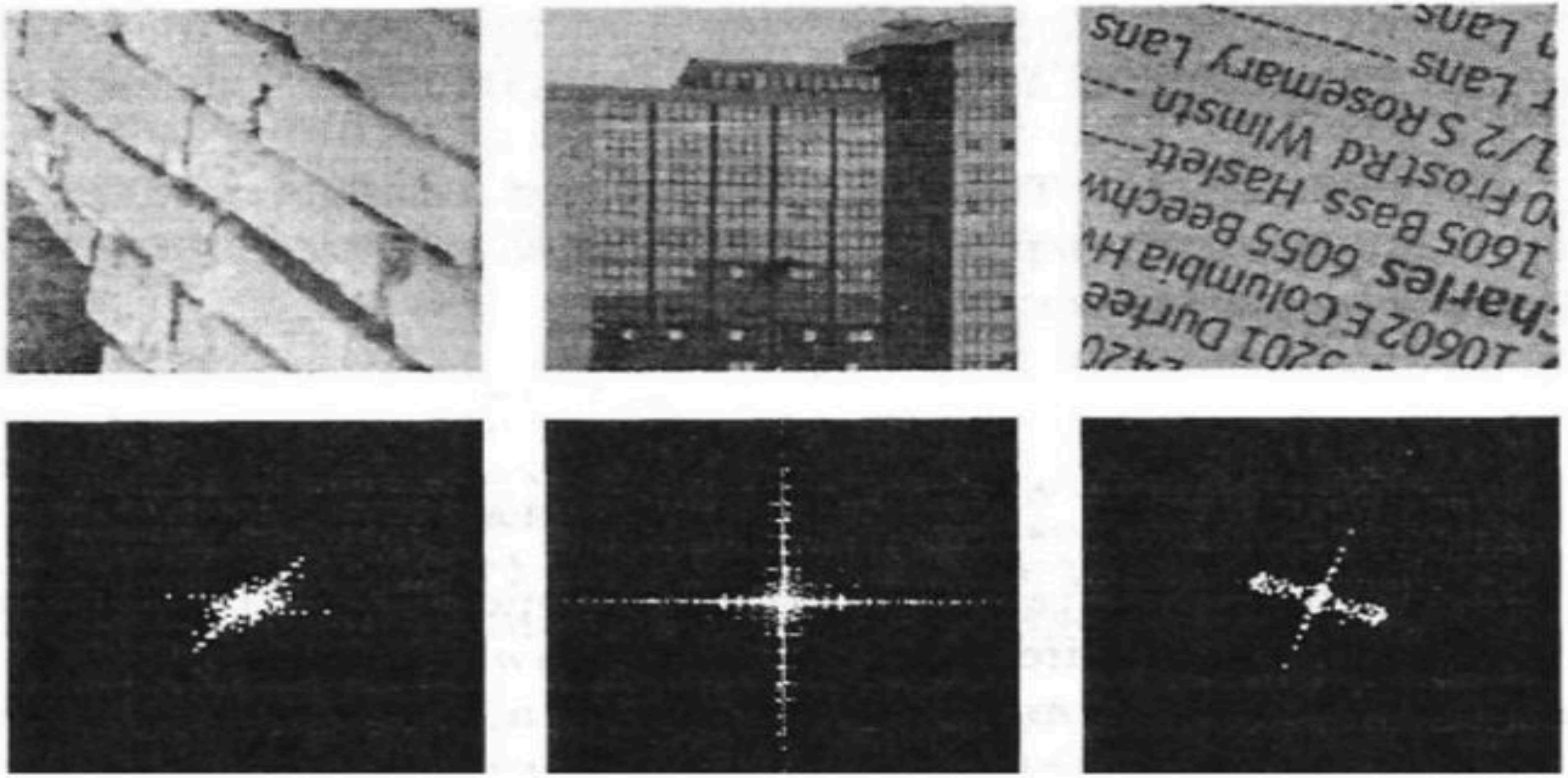


Power Spectrum and Texture

Concentrated power → regularity

High frequency power → fine texture

Directionality → directional texture



Summary

- Structural Approaches
- Statistical Approaches
  - Simple features
  - LBPs and GLCMs
  - Edge based features
  - Raw’ energy
- Interpreting Textures

Recommendations

- Paper reading for texture feature analysis
  - using gray level co-occurrence matrix
  - using Law’s texture energy
  - using edge-based features

- For example,
  - Texture features analysis using GLCM for abnormality detection in chest CT images (2018)
  - Image retrieval system, Fingerprint recognition and range image classification using GLCM