

CMP362/CMPN446: Image Processing and Computer Vision



Texture Analysis

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Agenda

- **What is Texture?**
- **Uses for Texture Analysis**
- **Texture Analysis Approaches**
 - Structural Approach
 - Statistical Approach
- **Statistical Texture Measures**
 - Edge Density and Directions
 - LBP Measure
 - GLCM
 - Laws' Texture Energy Features

What is Texture?

- a feature used to partition images into regions of interest and to classify those regions
- Texture is **a repeating pattern** of local variations in image intensity
- Image Texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image
- **cannot be defined for a point**

What is 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

Texture consists of **texture primitives** or texture elements, sometimes called **texels**.

- Texture features are found in **the tone** and **structure of a texture**.
- **Tone** is based on pixel intensity properties in the *texel*, while **structure** represents the spatial relationship between *texels*.

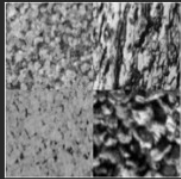
- Primitives in grass and dog fur are represented by several pixels and correspond to a stalk or a pile; cork is built from primitives that are comparable in size with pixels. **It is difficult**, however, to define primitives for the checkered textile or fabric, which can be defined by at least two hierarchical levels
- A texture primitive(Texels) is a contiguous set of pixels with some tonal and/or regional property, and can be described by its **average intensity, maximum or minimum intensity, size, shape, etc.** The spatial relationship of primitives can be random, or they may be pairwise dependent, or some number of primitives can be mutually dependent.
- Image texture is then described by the number and types of primitives and by their spatial relationship.

Texture can be described as fine, coarse, grained, smooth, etc.

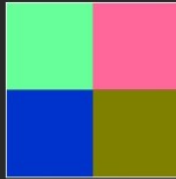
If texels are small and tonal differences between texels are large a fine texture results. – If texels are large and consist of several pixels, a coarse texture results.

Uses for Texture Analysis

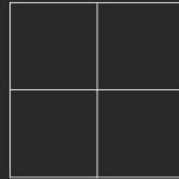
- Segment an image into regions with the same texture.
- Recognize or classify objects based on their texture .
- Find edges in an image, i.e. where the texture changes .
- "shape from texture"



Textured image



Region based texture
segmentation



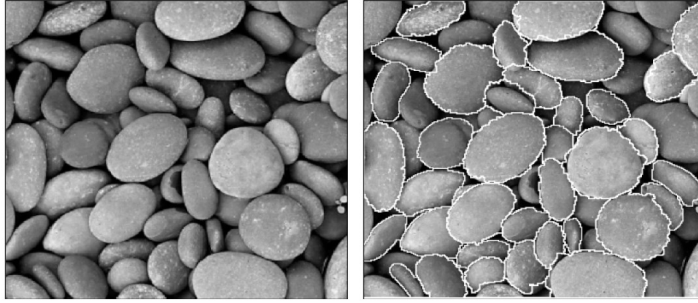
Texture Edge Detection

Texture Analysis Approaches

- **Structural Approach**
 - texture is a set of primitive texels in some regular or repeated relationship.
- **Statistical Approach**
 - texture is a **quantitative measure** of the **arrangement of intensities in a region**.
 - This set of measurements is called a feature vector.

Structural Approach

- A texture is a set of texture elements or texels occurring in some regular or repeated pattern



Problems with Structural Approach



What/Where are the texels?

Extracting texels in real images may be difficult or impossible

Statistical Approach

- 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**.

Statistical Texture Measures

- **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

Reference

<https://courses.cs.washington.edu/courses/se576/book/ch7.pdf>

Statistical Texture Measures

- **Edge Density and Direction**

- **Edgeness per unit area** : Given pixels P in a region

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

where N is the size of the image region being analyzed

- **Histogram of edge magnitude and directions in a region R**

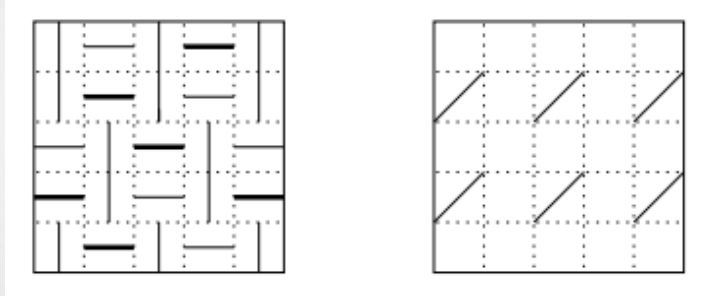
$$F_{\text{magdir}} = (H_{\text{magnitude}}(R), H_{\text{direction}}(R))$$

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

Edgeness per unit area measures the busyness, but not the orientation of the texture.

Statistical Texture Measures

- Edge Density and Direction

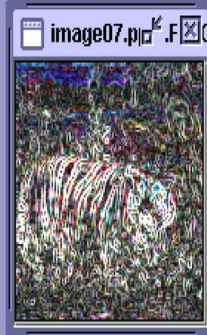


The image on the left is busier than the image on the right. It has an edge in every one of its 25 pixels, so its edgeness per unit area is 1.0. The image on the right has 6 edges out of its 25 pixels, so its edgeness per unit area is only 0.24.

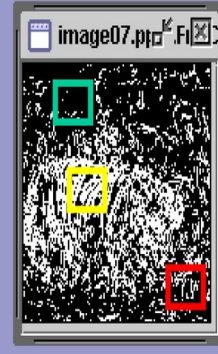
Original Image



Edge Image



Thresholded
Edge Image

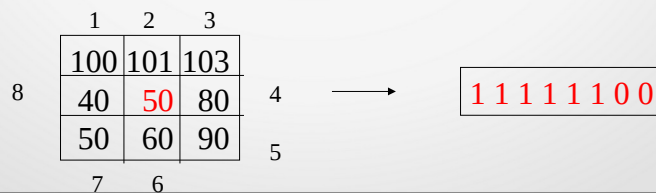


Different F_{edgeness} for different regions

Statistical Texture Measures

- Local Binary Pattern (LBP)**

- 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.



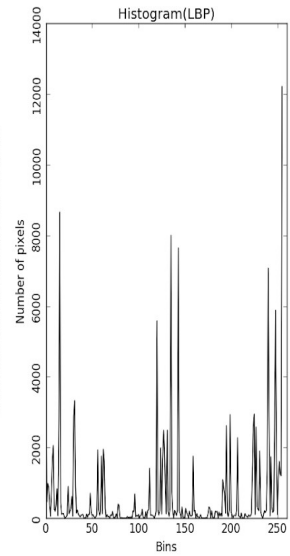
Two images or regions are compared by computing the L1 distance between their histograms as defined above.

LBP Example

Gray Image



LBP Image



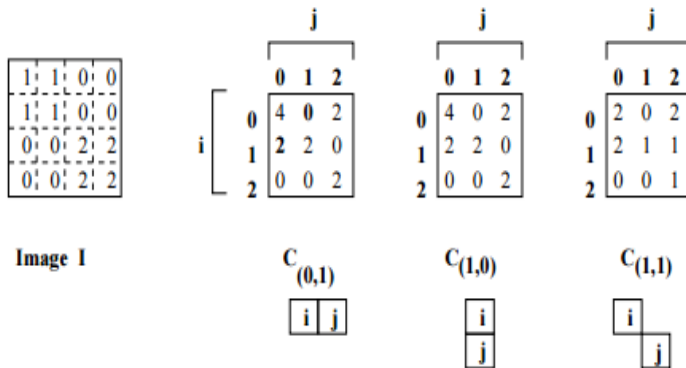
Statistical Texture Measures

- **GLCM (*Gray Level Co-occurrence Matrix*) Features**

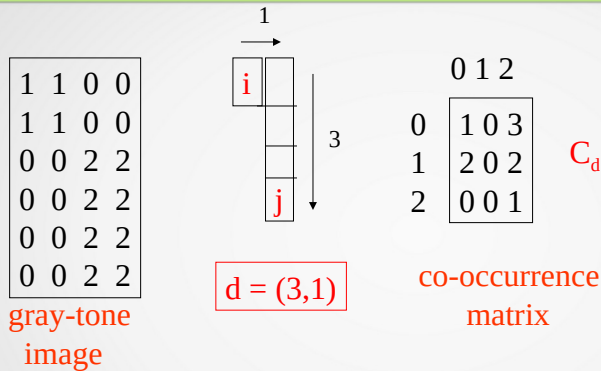
A co-occurrence matrix is a 2D array C in which

- 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 Matrix Example



Co-occurrence Matrix Example



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.

$$N_d(i, j) = \frac{C_d(i, j)}{\sum_i \sum_j C_d(i, j)}$$

Statistical Texture Measures

- **GLCM Features**

- Co-occurrence matrices capture properties of a texture, but **they are not directly useful** for further analysis, such as comparing two textures
- numeric features are computed from the co-occurrence matrix that can be used to represent the texture more compactly.

Statistical Texture Measures

- GLCM Features

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

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

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

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

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

where μ_i, μ_j are the means and σ_i, σ_j are the standard deviations of the row and column

1- Contrast: Contrast is a measure of intensity contrast between a pixel and its neighbor over the entire image. **If the image is constant, contrast equal 0** while **the biggest value** can be obtained **when the image is a random intensity image** and that pixel intensity and neighbor intensity are very different

2- Energy: Energy is a measure of uniformity where is **maximum** when the **image is constant** also called Uniformity . measures the textural uniformity that is pixel pair repetitions. It detects disorders in textures

3- Homogeneity: Homogeneity measures the spatial closeness of the distribution of the co-occurrence matrix. **Homogeneity equal 0** when the **distribution of the cooccurrence matrix is uniform** and **1** when the **distribution is only on the diagonal of the matrix**

4- Entropy: Entropy **measures the randomness** of the elements of the co-occurrence matrix. Entropy is **maximum** when **elements in the matrix are equal** while is equal to **0** if all **elements are different**. measures the disorder or complexity of an image. The entropy is large when the image is not texturally uniform and many GLCM elements have very small values. Complex textures tend to have high entropy

0	<- Measure ->	1
Constant Image	Contrast measure of intensity contrast between a pixel and its neighbor over the entire image	Random intensity image
Random Image	Energy measures the textural uniformity , detects disorders in textures	Constant Image
All elements in the matrix are different.	Entropy measures the randomness of the elements of the co-occurrence matrix	Elements in the matrix are equal (NO Peaks- Random)
Distribution of the co-occurrence matrix is uniform	Homogeneity measures the spatial closeness of the distribution of the co-occurrence matrix	The distribution is only on the diagonal of the matrix

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.

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.

Textures are made up of repeated local patterns, so: – Find the patterns

- Use filters that look like patterns (spots, bars, raw patches...)
- Consider magnitude of response

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

The L5 vector gives a center-weighted local average.

The E5 vector detects edges,
the S5 vector detects spots, and
the R5 vector detects ripples.

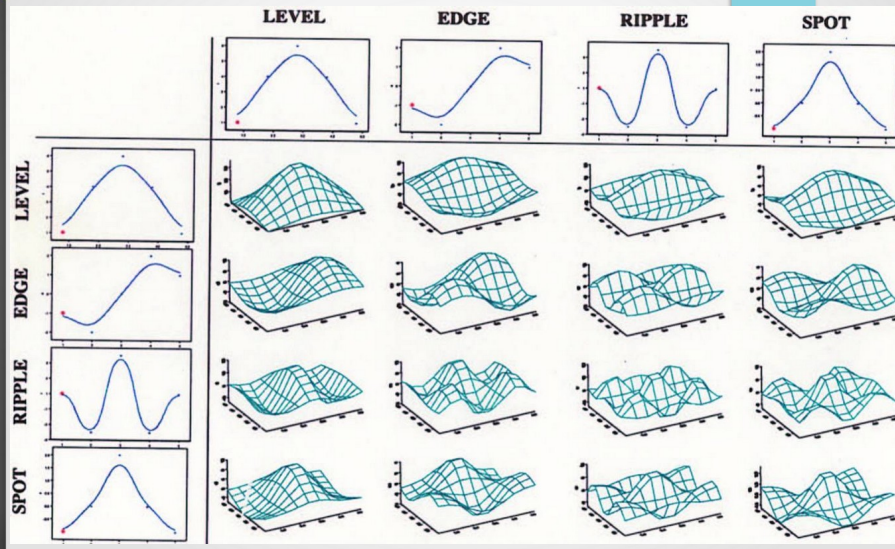
Law's texture masks (2)

Creation of 2D Masks

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

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

Laws Filters



9D feature vector for pixel

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

$$E_k[r,c] = \sum |F_k[i,j]|$$
- Replace each distinct pair with its average map
 - 9 features (9 filtered images) defined as follows:

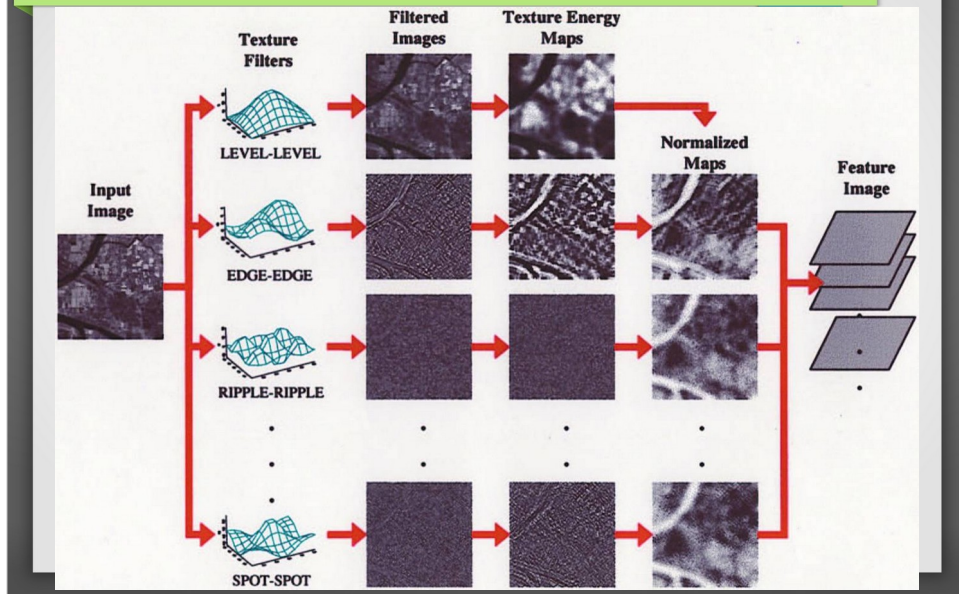
L5E5/E5L5	L5S5/S5L5
L5R5/R5L5	E5E5
E5S5/S5E5	E5R5/R5E5
S5S5	S5R5/R5S5
R5R5	

Step 1: The first step in Laws' procedure is to remove effects of illumination by moving a small window around the image, and subtracting the local average from each pixel, to produce a preprocessed image, in which the average intensity of each neighborhood is near to zero.

In step 3 each pixel will be replaced by the average of the absolute values of its neighbors in a window 15x15. this will generate 16 different images describing the texture energy of the image

In step 4 : Once the sixteen energy maps are produced, certain symmetric pairs are combined to produce the nine nal maps, replacing each pair with its average. For example, E5L5 measures horizontal edge content, and L5E5 measures vertical edge content. The average of these two maps measures total edge content.

Laws Process



Gabor filters are also texture filters