Texture

Soma Biswas
Department of Electrical Engineering,
Indian Institute of Science, Bangalore.
Definition and Applications

- Texture is a description of the spatial arrangement of color or intensities in an image or a selected region of an image.
- Can help segment images into regions of interest and classify them.

- Three very distinct textures – texture of tiger, jungle and water.
- Textures can be quantified and used to identify the object classes they represent.
Why Texture Analysis?

- Gives information about spatial arrangement of colors/intensities in image
- Histogram of a region: 50% white pixels and 50% black pixels
- Same intensity distribution, but 3 different textures

Figure 7.2: Three different textures with the same distribution of black and white.
Texture

- Commonly found in natural scenes – natural / man-made
- Different brick, leaf textures are different.
- Natural –large no. of small, round leaves, smaller no of larger, pointed leaves
- Thus textures descriptions more then just object classifications
- Man-made: primitive rectangular regions in white or black – easy to describe
- Visually see the spatial arrangement, but difficult to describe in words
**Texture Definition - Structural Approach**

**Definition:** Texture is a set of primitive texels in some regular or repeated relationship

- Describe the texels and specify the spatial relationship
- Texels must be segmentable and relationship must be efficiently computable
- Texels are extracted by simple means, eg. Thresholding
- Spatial relationship is given by Voronoi tessellation
- Voronoi polygon is the polygonal region consisting of all points that are closer to P that to any other point
- Shape features of the polygons are calculated and used to group the polygons into clusters that define uniformly textured surfaces
- Work well for man-made regular textures.
Problem with Structural Approach

- How do you decide what is a texel?

![Grass](image1.png)  ![Leaves](image2.png)

**grass**  **leaves**
Texture Definition - Statistical Approach

**Definition:** Texture is a quantitative measure of the arrangement of intensities in a region.

- 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 Approach

1. Edge density and direction
2. Local binary partition
3. Co-occurrence matrices and features
4. Laws texture energy measures
5. Autocorrelation
Edge Density and Direction

- Use an edge detector as the first step in texture analysis.
- 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

1. edgeness per unit area – measures busyness not orientation of texture

\[
\text{Fedgeness} = \frac{|\{ p \mid \text{gradient}\_\text{magnitude}(p) \geq \text{threshold}\}|}{N}
\]

2. edge magnitude and direction histograms

\[
\text{Fmagdir} = (\text{Hmagnitude}, \text{Hdirection})
\]

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

Region of N pixels
Gradient-based edge detector produces 2 outputs for each pixel (p)
- Gradient magnitude
- Gradient Direction
- T - threshold
Edge Density and Direction

- Left image busier than right one
- Gradient magnitude Histograms: 2 bins representing dark edges & light edges
- Gradient direction histograms: 3 bins: horizontal, vertical and diagonal edges

\[
\begin{align*}
F_e &= \frac{25}{25} \\
H_m &= \frac{(6,19)}{25} \\
H_d &= \frac{(12,13,0)}{25}
\end{align*}
\]

\[
\begin{align*}
F_e &= \frac{6}{25} \\
H_m &= \frac{(0,6)}{25} \\
H_d &= \frac{(0,0,6)}{25}
\end{align*}
\]

\[L_1(H_1, H_2) = \sum_{i=1}^{n} | H_1[i] - H_2[i] |\]
Local Binary Pattern

• 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.

Fig. 2. The circular (8,1), (16,2) and (8,2) neighborhoods. The pixel values are bilinearly interpolated whenever the sampling point is not in the center of a pixel.
Extensions of LBP - Uniform Patterns

- LBP called uniform if the binary pattern contains at most two bitwise transitions from 0 to 1 or vice versa when the bit pattern is considered circular.

- Patterns 00000000 (0 transitions), 01110000 (2 transitions) and 11001111 (2 transitions) are uniform.

- Patterns 11001001 (4 transitions) and 01010011 (6 transitions) are not.

- In the computation of the LBP histogram, uniform patterns are used so that the histogram has a separate bin for every uniform pattern and all non-uniform patterns are assigned to a single bin.

- Experiments show that uniform patterns account for little less than 90% of all patterns when using the (8,1) neighborhood and for around 70% in the (16,2) neighborhood.
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.

Low-level measures don’t always find semantically similar images.
Gray Level Co-occurrence Matrix

- Texture is a spatial property
- Spatial dependence of gray-level values which contribute to the perception of texture – a 2d dependence matrix is GLCM
- A co-occurrence matrix is a 2D array C in which

  - Both the rows and columns represent a set of possible image values
  - \( C(i,j) \) 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 \( d = (dr,dc) \).
GLCM

\[ d = (1,1) \]

- Normalized co-occurrence matrix - where each value is divided by the sum of all the values.
GLCM

- Gray-level co-occurrence matrix captures the spatial distribution of gray levels
- 8x8 binary image of checker board - 2 gray levels – so $P(i,j)$ is 2x2 matrix
- If the black pixels are randomly distributed throughout the image with no fixed structure, the GLCM will not have any preferred set of gray-level pairs. --> In such a case the matrix is expected to be uniformly populated.
Co-occurrence Features

\[
\begin{align*}
\text{Energy} & = \sum_i \sum_j N^2_d(i, j) \\
\text{Entropy} & = -\sum_i \sum_j N_d(i, j) \log_2 N_d(i, j) \\
\text{Contrast} & = \sum_i \sum_j (i - j)^2 N_d(i, j) \\
\text{Homogeneity} & = \sum_i \sum_j \frac{N_d(i, j)}{1 + |i - j|} \\
\text{Correlation} & = \frac{\sum_i \sum_j (i - \mu_i)(j - \mu_j) N_d(i, j)}{\sigma_i \sigma_j}
\end{align*}
\]  

(7.7)  

(7.8)  

(7.9)  

(7.10)  

(7.11)

where \( \mu_i, \mu_j \) are the means and \( \sigma_i, \sigma_j \) are the standard deviations of the row and column

choose the displacement vector \( d \). A solution suggested by Zucker and Terzopoulos is to use a \( \chi^2 \) statistical test to select the value(s) of \( d \) that have the most structure; that is, to maximize the value:

\[
\chi^2(d) = \left( \sum_i \sum_j \frac{N^2_d(i, j)}{N_d(i)N_d(j)} - 1 \right)
\]
Discussion - GLCM

- Entropy is highest when all entries in $P[i,j]$ are equal; -> matrix corresponds to an image in with no preferred gray-level pairs for the $d$.
- The choice of $d$ is an important parameter in the definition of GLCM
- GLCM particularly suitable for describing microtextures.
- Applications: extensively in remote sensing applications for land-use classification.

Normalized co-occurrence matrix

$$N_d[i, j] = \frac{C_d[i, j]}{\sum_i \sum_j C_d[i, j]}$$

Symmetric co-occurrence matrix

$$S_d[i, j] = C_d[i, j] + C_{-d}[i, j]$$
Laws’ Texture Energy Features

- Use local masks to detect various types of texture
- Measures the amount of variation within a fixed-size window

**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.

<table>
<thead>
<tr>
<th>Mask</th>
<th>Type</th>
<th>Filter Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>L5</td>
<td>Level</td>
<td>1 4 6 4 1</td>
</tr>
<tr>
<td>E5</td>
<td>Edge</td>
<td>-1 -2 0 2 1</td>
</tr>
<tr>
<td>S5</td>
<td>Spot</td>
<td>-1 0 2 0 -1</td>
</tr>
<tr>
<td>R5</td>
<td>Ripple</td>
<td>1 -4 6 -4 1</td>
</tr>
</tbody>
</table>

**Law’s texture masks**

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

- Create 2D masks – computing outer product of vector pairs

**1D Masks are “multiplied” to construct 2D masks:**

mask E5L5 is the “product” of E5 and L5 –

\[
\begin{bmatrix}
-1 \\
-2 \\
0 \\
2 \\
1
\end{bmatrix} \times \begin{bmatrix}
1 & 4 & 6 & 4 & 1
\end{bmatrix} = \begin{bmatrix}
-1 & -4 & -6 & -4 & -1 \\
-2 & -8 & -12 & -8 & -1 \\
0 & 0 & 0 & 0 & 0 \\
2 & 8 & 12 & 8 & 2 \\
1 & 4 & 6 & 4 & 1
\end{bmatrix}
\]
Steps in Laws algorithm

- Remove illumination effects - move a small window around the image and subtract local average from pixel
- Dot product 16 5x5 masks with neighborhood
- Texture energy map for filter k (Fk : filtered output)  
  \[ E_k[r, c] = \sum_{j=r-7}^{r+7} \sum_{i=c-7}^{c+7} |F_k[i,j]| \]
- 9 features defined as follows:

  \[
  \begin{align*}
  &L5E5/E5L5 & \quad &L5S5/S5L5 \\
  &L5R5/R5L5 & \quad &E5E5 \\
  &E5S5/S5E5 & \quad &E5R5/R5E5 \\
  &S5S5 & \quad &S5R5/R5S5 \\
  &R5R5 &
  \end{align*}
  \]
Sample Images

(a) Original image
(b) Segmentation into 4 clusters
(c) Original image
(d) Segmentation into 4 clusters
(e) Original image
(f) Segmentation into 3 clusters

water

tiger

fence

flag

grass

small flowers

big flowers
Features from sample images

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

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

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

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

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

function $\rho(dr, dc)$ of an $N + 1 \times N + 1$ image for displacement $d = (dr, dc)$ is given by

$$\rho(dr, dc) = \frac{\sum_{r=0}^{N} \sum_{c=0}^{N} I[r,c]I[r+dr,c+dc]}{\sum_{r=0}^{N} \sum_{c=0}^{N} I^2[r,c]}$$

(7.13)

$$= \frac{I[r,c]I_a[r,c]}{I[r,c]I[r,c]}$$

(7.14)

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

- **Face Recognition:** build several local descriptions of the face and combine them into a global description
- Holistic description of face using texture methods not reasonable -> texture descriptors tend to average over the image area.

- **Spatially enhanced histogram:** encodes both appearance & spatial relations of facial regions
- Description of the face: LBP labels contain information about the patterns on a pixel-level, the labels summed over a small region produce information on a regional level; regional histograms concatenated to get global description of the face.
LBP: Application to Face Recognition

- Each element in the enhanced histogram corresponds to a small area of the face.
- Psychophysical findings: some facial features (e.g., eyes) play more important roles in FR than other features.
- The regions can be weighted based on the importance of the area for FR.

For example, the weighted Chi square distance

$$
\chi^2_w(x, \xi) = \sum_{j,i} w_j \frac{(x_{i,j} - \xi_{i,j})^2}{x_{i,j} + \xi_{i,j}}.
$$

Fig. 4. (a) A facial image divided into 7x7 windows. (b) The weights set for the weighted $\chi^2$ dissimilarity measure. Black squares indicate weight 0.0, dark gray 1.0, light gray 2.0 and white 4.0.
LBP: Applications to Medical Images

- medical image annotation.
- Breast cancer classification - tissue information used to classify lesions to reduce unnecessary biopsies.
- MRI (Magnetic Resonance Imaging) – brain image analysis
- Ultrasound Images - non-invasive low-cost imaging solution to primary care diagnostics; inherent speckle noise - > uncertainty in the representation of their textural characteristics – Fuzzy LBP

Examples of images belonging to the three types of areas (see text for more details). (a) Building. (b) Woodland. (c) Farmland. (d) Water
GLCM

- ICME 2012 - Crowd density estimation is important for intelligent video surveillance - Local Binary Pattern (LBP) Co-occurrence Matrix (LBPCM) for crowd density estimation.

- Higher-order Co-occurrence Features based on Discriminative Co-clusters for Image classification – BMVC 2012

- Face Recognition using Gray level Co-occurrence Matrix and Snap Shot Method of the Eigen Face – 2012

- Abdominal Tumor Characterization and Recognition Using Superior-Order Co-occurrence Matrices, Based on Ultrasound Images - 2011

- Identification of masses in digital mammogram using gray level co-occurrence matrices – 2009

- Ovarian Cancer Detection