Chapter 16

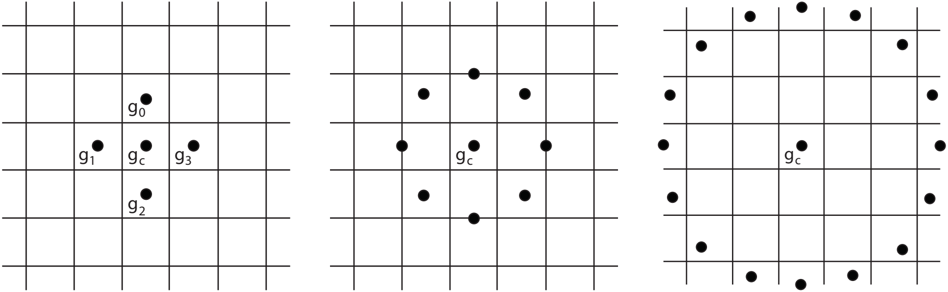
Texture

16.0.1 Local Binary Patterns—LBPs

- Local Binary Patterns (LBP) motivated by three-valued texture units
- Main idea is to locally threshold the brightness of a pixel's neighborhood at the center pixel gray level to form a binary pattern.
- LBP operator is gray-scale invariant and is derived as follows:
  texture is described in a local neighborhood of a central pixel, the neighborhood consisting of P ($P > 1$) equally spaced points on a circle of radius $R > 0$ centered at the center pixel.
- Texture is described as a joint distribution

$$T = t(g_c, g_0, g_1, ..., g_{P-1}), \tag{16.1}$$

  where g_c is the gray level of the central pixel and $g_0, ..., g_{P-1}$ are gray values of the neighborhood pixels.
- Assuming coordinates of G_c are (0,0), coordinates of the neighborhood pixels g_p are given by $[-R\sin(2\pi p/P), R\cos(2\pi p/P)]$.
- If point does not fall exactly at the center of a pixel, its value is estimated by interpolation (Fig. 16.1).



(a) P=4, R=1.0 (b) P=8, R=1.5 (c) P=16, R=3.0

Figure 16.1: Circularly symmetric neighborhoods for different values of P and R

- gray-scale invariance via using gray-level differences rather than brightness values:

$$T = t(g_c, g_0 - g_c, g_1 - g_c, ..., g_{P-1} - g_c)\,. \tag{16.2}$$

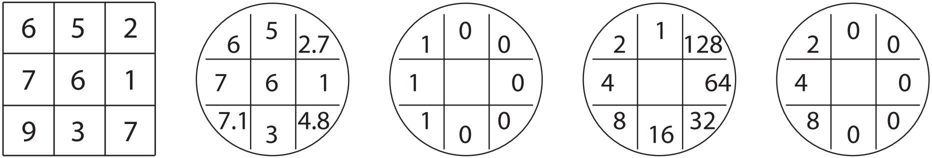
- assuming that brightness g_c is independent of the differences $g_p - g_c$ (not exactly true), texture can be represented as:

$$T \approx t(g_c)t(g_0 - g_c, g_1 - g_c, ..., g_{P-1} - g_c)\,, \tag{16.3}$$

- image luminance ... $t(g_c)$
  texture ... brightness differences between central and neighboring pixels
- luminance does not contribute to texture properties, texture description can be based on differences only:

$$T \approx t(g_0 - g_c, g_1 - g_c, ..., g_{P-1} - g_c)\,. \tag{16.4}$$

- texture description ... calculating occurrences of neighborhood brightness patterns in P-dimensional histogram.
  - all differences are zero for a constant-brightness region
  - high in all directions for a spot located at g_c
  - exhibit varying values along local image edges
- this histogram can be used for texture discrimination
- such a description is invariant to brightness shifts



(a) (b) (c) (d) (e)

Figure 16.2: Binary texture description operator $LBP_{8,1}$. (a) Original gray values of a 3×3 image. (b) Gray-level interpolation achieves symmetric circular behavior. Linear interpolation was used for simplicity. (c) Circular operator values after binarization, equations (16.5–16.6). (d) Directional weights. (e) Directional values associated with $LBP_{8,1}$—the resulting value of $LBP_{8,1} = 14$. If rotationally normalized, the weighting mask would rotate by one position counterclockwise, yielding $LBP^{ri}_{8,1} = 7$.

- to achieve invariance to brightness scaling, the absolute values of gray level differences may be replaced with their signs as shown in Fig. 16.2a,b.

$$T \approx t(s(g_0 - g_c), s(g_1 - g_c), ..., s(g_{P-1} - g_c)) \tag{16.5}$$

where

$$s(x) = \begin{cases} 1 & \text{for } x \geq 0 \\ 0 & \text{for } x < 0 \end{cases} . \tag{16.6}$$

- ordering operator elements to form a circular chain with values of zero and one, specific directions can be consistently weighted forming a scalar chain code descriptor
- chain code contributors can be summed over the entire circular neighborhood of P pixels as depicted on Fig. 16.2c,d
- local texture pattern can be described by a single number for any specific (P, R) combination.
- weights 2^p can be assigned in a circular fashion with p increasing for all P points.

$$\mathrm{LBP}_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c) 2^p \,. \tag{16.7}$$

- for a texture patch, these $\mathrm{LBP}_{P,R}$ values can be used to form single- or multi-dimensional histograms or feature vectors
- or can be further processed to become rotation and/or spatial scale invariant as described below

- When the image is rotated, image gray values travel around the circle, affecting the LBP values
- to achieve rotational invariance it is natural to normalize the circular chain code in a way minimizes the resulting LBP^{ri} value (Fig. 16.2

$$\mathrm{LBP}^{ri}_{P,R} = \min_{i=0,1,\ldots,P-1} \{ROR(\mathrm{LBP}_{P,R}, i)\}\,, \tag{16.8}$$

  where $ROR(x, i)$ denotes a circular bitwise right shift on the P-bit number x i-times—or simply rotating the circular neighbor set clockwise so that the resulting LBP value is minimized.
- patterns $\mathrm{LBP}^{ri}_{P,R}$ can be used as feature detectors
- for $\mathrm{LBP}^{ri}_{8,1}$, 36 such feature detectors can be formed as shown in Fig. 16.3. Pattern #0 would indicate a bright spot location, #8 a dark spot location flat areas, #4 corresponds to straight edges, etc.

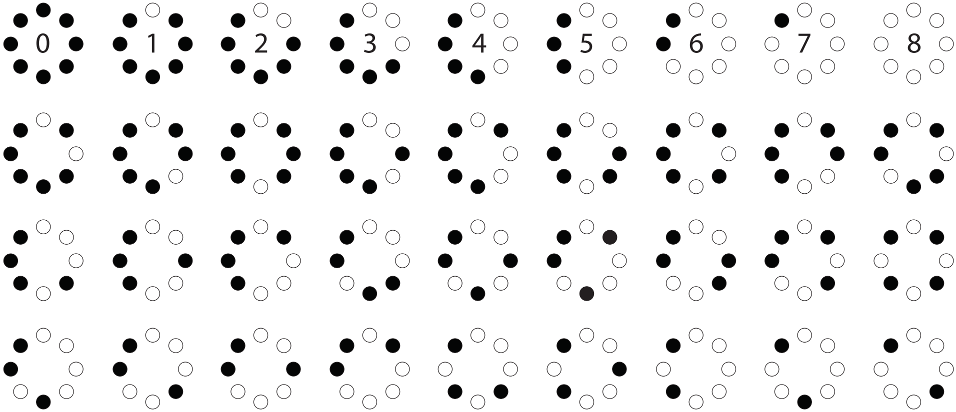


Figure 16.3: For $\mathrm{LBP}^{ri}_{8,R}$, 36 unique circularly symmetric feature detectors can be formed: black and white circles correspond to bit values The first row shows the 9 "uniform" patterns with their $\mathrm{LBP}^{riu2}_{8,R}$ values shown. Adapted from [Ojala et al., 2002b].

- $\mathrm{LBP}^{ri}_{8,1}$ features do not perform very well in real-world problems [Pietikainen et al., 2000]
- however, local binary patterns can be derived from $\mathrm{LBP}^{ri}_{8,1}$ features to represent fundamental texture properties
- $\Longrightarrow$ **uniform patterns** ... have uniform circular structure with minimal spatial transitions
- for $\mathrm{LBP}^{ri}_{8,R}$, such uniform patterns are shown in the first row of Fig. 16.3
- the uniform patterns can be considered **microstructure templates** with the same interpretation as given above
  - #0 being a bright spot microtemplate, etc.
- **uniformity measure** U can be introduced
  reflecting the number of 0/1 (or 1/0) transitions
  - all the uniform patterns have U values of 2 or less
  - all other patterns have a U value of at least 4

$\Longrightarrow$ gray-scale and rotation invariant texture descriptor is defined as

$$\mathrm{LBP}_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c) & \text{if } U(\mathrm{LBP}_{P,R}) \leq 2 \\ P+1 & \text{otherwise} \end{cases}, \tag{16.9}$$

where

$$U(\mathrm{LBP}_{P,R}) = |s(g_{P-1}-g_c)-s(g_0-g_c)|+\sum_{p=1}^{P-1}|s(g_p-g_c)-s(g_{p-1}-g_c)|\,. \tag{16.10}$$

Here, superscript $riu2$ denotes rotational invariant uniform patterns with uniformity values of at most 2.

- only P+2 patterns can exist:
  - P+1 uniform patterns
  - one additional 'catch-all' pattern (Fig. 16.3)
- mapping from $\mathrm{LBP}_{P,R}$ to $\mathrm{LBP}_{P,R}^{riu2}$ is best implemented using a look-up table with 2^P elements.

- texture description based on a histogram of $\mathrm{LBP}_{P,R}^{riu2}$ operator outputs accumulated over a texture patch
- this approach works much better than using $\mathrm{LBP}_{P,R}^{ri}$ features directly due to a overwhelmingly larger proportion of uniform patterns when collecting the microstructure templates
- their relatively low occurrence frequencies, statistical properties of 'non-uniform' patterns cannot be reliably estimated and resulting noisy estimates negatively influence texture discrimination
- e.g., when analyzing Brodatz textures, $\mathrm{LBP}_{8,1}^{ri}$ features consist of 87% uniform and only 13% non-uniform patterns
- since only 9 uniform templates exist while three times as many (27) non-uniform templates can be formed, the frequency differences become even more striking
- similarly, the uniform/non-uniform frequency distributions are 67–33% for $\mathrm{LBP}_{16,2}^{ri}$ and 50–50% for $\mathrm{LBP}_{24,3}^{ri}$ on the same set of textures
- these distributions seem quite stable across different texture discrimination problems [Ojala et al., 2002b].

- choice of P and R
  - increasing P helps with overcoming the crudeness of angular quantization
  - P and R are related in the sense that the radius must increase proportionally with denser angular sampling or the number of non-redundant pixel values in the circular neighborhood will become a limiting factor (nine non-redundant pixels are available for $R = 1$)
  - if P is increased too much, the size 2^P of the look-up table will affect computational efficiency
- practical experiments limited P values to 24 [Ojala et al., 2002b], resulting in a 16MB look-up table, an easily manageable size

- using LBP features and pattern histograms for texture classification, non-parametric statistical tests were employed to determine dissimilarity of the histogram description from all model histograms of LBP features obtained during training
- the lowest (and perhaps below-minimum threshold) dissimilarity criterion identifies the most likely texture class the patch sample belongs to
- this has an additional advantage of permitting an ordering of the most likely classifications according to their likelihood
- non-parametric statistical tests like chi-square or G (log-likelihood ratio) can be used to assess the goodness of fit.

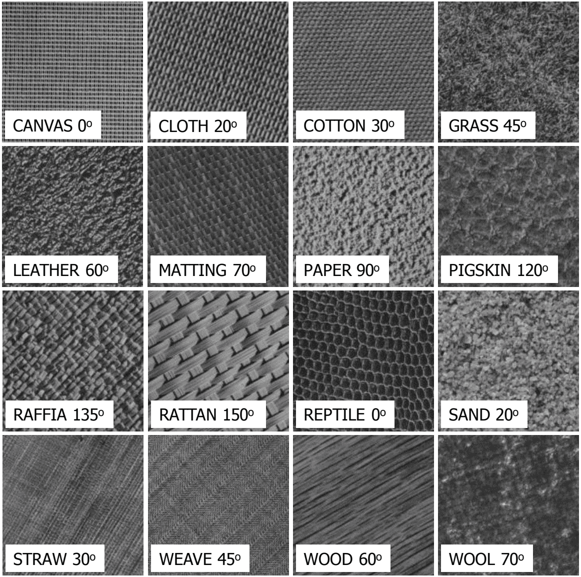


Figure 16.4: Samples of 16 Brodatz textures used for $\mathrm{LBP}_{P,R}^{riu2}$ evaluation in [Ojala et al., 2002b]. Patches shown are 180×180 pixels and were rotated at different angles in addition to the angular rotations depicted in the figure. Courtesy of Matti Piteikainen and Timo Ojala, Oulu University, Finland.

- when applied to classification of 16 Brodatz textures (Fig. 16.4), the $\mathrm{LBP}_{P,R}^{riu2}$ histograms, followed by goodness-of-fit analysis, outperformed wavelet transforms, Gabor transforms, and Gaussian Markov Random Field approaches while exhibiting the lowest computational complexity

- rotational invariance was demonstrated by training the LBP method in textures of single orientation and testing independent samples rotated using 6 different angles (Fig. 16.4). $\mathrm{LBP}_{8,1}^{riu2}$, $\mathrm{LBP}_{16,2}^{riu2}$, and $\mathrm{LBP}_{24,3}^{riu2}$ were used

- 100% classification was achieved for some feature combinations including variance measures, compared with the second best 95.8% reported in [Porter and Canagarajah, 1997], achieved using wavelets. Another set of experiments used 24 classes of natural textures acquired using a robotic arm-mounted camera at different angles and with varying controlled illumination

- the LBP method demonstrated excellent performance

- test image data and the texture classification software test suite *OUTEX* can be accessed at http://www.outex.oulu.fi/ [Ojala et al., 2002a].

- An interesting adaption of these ideas has constructed LBPs of gradient images to assist in face recognition [Vu et al., 2012]

- — gradient LBPs were supplemented by Gaussian Mixture Models – GMMs and Support Vector Machines – SVMs —proves very fast and efficient, outperforming comparable techniques in performance as well

16.1 References

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