Feature Extraction — Texture: GLCM and LBP

1. Introduction to Texture Feature Extraction

Texture refers to the spatial arrangement and repetition of intensity patterns/gray-level variations in an image. It is an important region descriptor that provides measures such as smoothness, coarseness, and regularity, which cannot be captured by amplitude (intensity) alone.

Texture description approaches are broadly classified as:

- Statistical approaches — describe texture using statistical properties of gray levels (e.g., moments, GLCM).
- Structural approaches — describe texture in terms of arrangement of well-defined primitives (texels) following placement rules.
- Spectral approaches — use properties of the Fourier spectrum to detect global periodicity.

Two of the most widely used statistical/local-pattern texture descriptors are the Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP), described below.

2. Gray-Level Co-occurrence Matrix (GLCM)

Proposed by Haralick, GLCM is a second-order statistical texture analysis method that considers the spatial relationship between pairs of pixels. It computes how often a pixel with gray-level value i occurs in a specific spatial relationship (distance d and direction θ) with a pixel of gray-level value j.

2.1 Construction of GLCM

For an image with L gray levels, the GLCM is an L×L matrix $P(i, j \mid d, \theta)$, where each entry represents the number (or probability, after normalization) of times a pixel pair with values (i, j) occurs separated by distance d in direction θ.

Steps to construct GLCM:

1. Select displacement vector (d, θ) — common directions: 0°, 45°, 90°, 135°.

2. Scan the image and, for every pixel pair separated by (d, θ), increment the corresponding matrix entry P(i, j).

3. Normalize the matrix by dividing each entry by the total number of pixel pairs, so that $\Sigma_i\Sigma_j P(i,j) = 1$.

4. Often GLCM is computed for multiple directions and averaged, to achieve approximate rotation invariance.

2.2 Haralick Texture Features Derived from GLCM

Once normalized, statistical features are computed from the GLCM to numerically describe the texture:

Feature	Formula	Meaning
Energy / ASM	$\Sigma_i\Sigma_j P(i,j)^2$	Textural uniformity / homogeneity of pixel pairs
Contrast	$\Sigma_i\Sigma_j (i-j)^2 P(i,j)$	Local intensity variation / amount of texture
Correlation	$\Sigma_i\Sigma_j [(i-\mu i)(j-\mu j)P(i,j)] / \sigma i\sigma j$	Linear dependency of gray levels of neighboring pixels
Homogeneity (IDM)	$\Sigma_i\Sigma_j P(i,j) / [1+(i-j)^2]$	Closeness of distribution of elements to the diagonal
Entropy	$-\Sigma_i\Sigma_j P(i,j) \log P(i,j)$	Randomness / complexity of the texture

Other Haralick features include: Sum of Squares (Variance), Sum Average, Sum Entropy, Difference Variance, Difference Entropy, Maximum Probability, and Cluster Shade/Prominence.

2.3 Advantages and Limitations

- Advantages: Captures spatial relationships between pixels; provides rich, well-established statistical descriptors; widely validated in medical imaging, remote sensing, and material analysis.
- Limitations: Computationally expensive for large images/gray-level ranges; matrix size grows with gray levels (often requires gray-level quantization); sensitive to noise and choice of (d, θ).

3. Local Binary Pattern (LBP)

Proposed by Ojala et al., LBP is a simple yet powerful local texture descriptor that encodes the local spatial structure of an image by thresholding the neighborhood of each pixel against the center pixel's value.

3.1 Basic LBP Operator

For a center pixel gc with neighboring pixels gp (p = 0, 1, …, P−1) sampled on a circle of radius R:

$$LBP(P,R) = \Sigma_{p=0}\text{^}(P-1)\ s(gp - gc) \times 2^p$$

$$s(x) = 1 \text{ if } x \geq 0;\ s(x) = 0 \text{ if } x < 0$$

In the classic 3×3 case (P = 8, R = 1): the 8 surrounding pixels are compared to the center pixel; each neighbor is assigned 1 if its value ≥ center, else 0. The resulting 8-bit binary string (read in a fixed order) is converted to a decimal number — the LBP code — which replaces the center pixel.

3.2 Steps to Compute LBP

1. For each pixel, select its P neighbors on a circle of radius R (using interpolation for non-integer coordinates).
2. Threshold each neighbor against the center pixel value to get a binary pattern.
3. Convert the binary pattern into a decimal LBP code using positional weights (powers of 2).
4. Replace each pixel with its computed LBP code, forming an LBP image.
5. Build a histogram of LBP codes over the image (or over sub-regions/blocks) — this histogram is the texture feature vector.

3.3 Variants of LBP

- Uniform LBP — patterns with at most two 0-1 or 1-0 transitions in the circular binary string; reduces feature dimensionality and noise sensitivity while retaining most texture information.
- Rotation-Invariant LBP — circularly shifts the binary code to its minimum value, making the descriptor invariant to image rotation.
- Multi-scale / Multi-resolution LBP — uses multiple (P, R) combinations to capture texture at different scales.
- Extensions — LBP variance (LBPV), Complete LBP (CLBP), and combining LBP with contrast measures for richer descriptors.

3.4 Advantages and Limitations

- Advantages: Computationally simple and fast; invariant to monotonic gray-scale (illumination) changes; effective for real-time applications (face recognition, defect/anomaly detection).

- Limitations: Sensitive to image noise (since it relies on exact pixel comparisons); basic LBP is not rotation invariant unless a rotation-invariant variant is used; may lose some global structural texture information captured by GLCM.

4. Comparison: GLCM vs LBP

Aspect	GLCM	LBP
Basis	Second-order statistics (pixel-pair co-occurrence)	First-order local micro-pattern encoding
Computation	Builds a co-occurrence matrix, derives statistical features	Thresholds each pixel's neighborhood, forms a binary/decimal code
Output	Set of scalar statistical features (contrast, energy, etc.)	Histogram of LBP codes
Computational cost	Higher — matrix construction + statistics per direction/distance	Lower — simple comparisons, fast and efficient
Rotation invariance	Not inherently rotation invariant (depends on direction θ)	Achievable using rotation-invariant LBP variants
Robustness	Sensitive to noise and illumination changes	Illumination invariant (grayscale monotonic transform invariant)
Typical use	Medical imaging, remote sensing, material classification	Face recognition, texture classification, defect detection

5. Applications of Texture Feature Extraction

- Medical image analysis — classification of tumors/tissues based on texture (e.g., MRI, CT, mammography).
- Remote sensing — land-cover/land-use classification from satellite imagery.
- Face recognition and biometrics — LBP-based facial texture descriptors.
- Industrial inspection — surface defect detection (fabric, wood, metal surfaces).
- Content-based image retrieval (CBIR) — retrieving images with similar texture content.

6. Conclusion

Texture is a vital region descriptor in image analysis, and GLCM and LBP represent two complementary approaches to extracting it. GLCM captures rich second-order spatial statistics between pixel pairs and yields well-established Haralick features, making it suitable for detailed statistical texture analysis, while LBP offers a computationally efficient, illumination-invariant local pattern encoding well-suited to real-time and biometric applications. In practice, the two are often combined to leverage both global statistical structure and fine local texture detail for robust feature extraction.