Texture classification using Local Binary Patterns

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Overview

Problem statement

- **Goal:** Classify textures (13 Brodatz textures) invariant to rotation using local image descriptors.
- **Approach:** Use Local Binary Patterns (LBP) and rotation-invariant / multi-resolution variants, optionally combined with local variance (VAR) and probabilistic histogram-based classification.

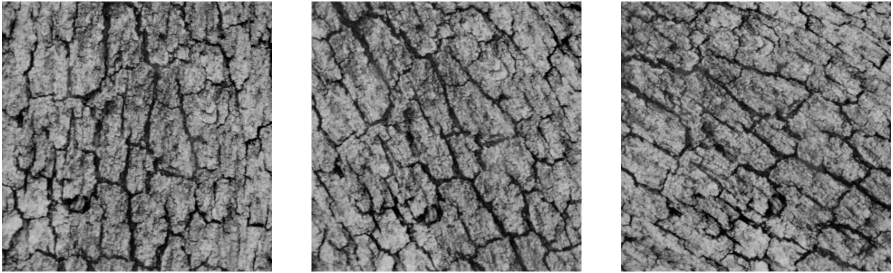


Figure 1: Rotation variants of the Bark texture from Brodatz dataset [2]

Local Binary Patterns (intuition)

- At each pixel, compare its intensity g_c with P circular neighbors g_p at radius R.
- Create a binary code using thresholding:

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$$

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

- This encodes local texture structure like edges, corners, and spots.

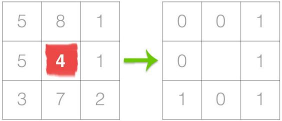


Figure 2: Thresholding neighbor pixels around the center pixel [3].

LBP Encoding: Bit Ordering

- After thresholding, the binary values are arranged in a fixed circular order.
- Each neighbor contributes a weighted bit: $2^0, 2^1, \ldots, 2^{P-1}$.
- The final LBP value is a binary-to-decimal conversion of these bits.

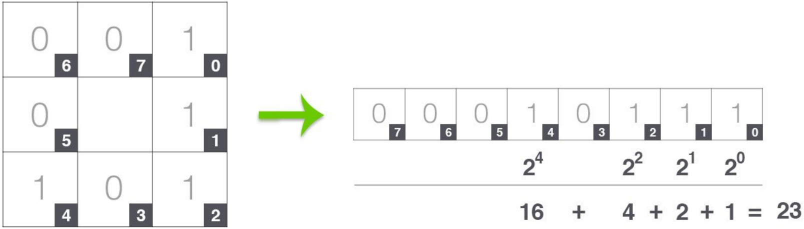


Figure 3: LBP bit indexing and weighted binary encoding [3].

LBP on Full Image

- The process is repeated for every pixel in the image.
- Each pixel is replaced by its LBP code, generating the LBP image.
- This image captures local texture patterns invariant to monotonic gray-scale changes.

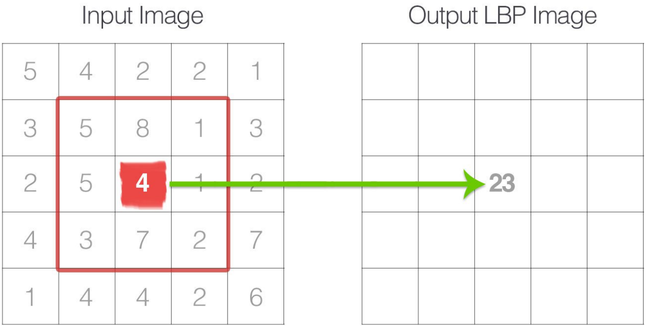


Figure 4: LBP applied to the full image, producing the LBP map [3].

Rotation Invariant LBP: Circular Neighborhood

- For generalized LBP, neighbors lie on a **circle** of radius R around the center pixel.
- Number of neighbors: P, evenly spaced with angle:

$$\theta_p = \frac{2\pi p}{P}, \quad p = 0, \ldots, P-1$$

- Non-integer pixel locations are handled using bilinear interpolation.
- Increasing P and R gives **multi-resolution texture description**.

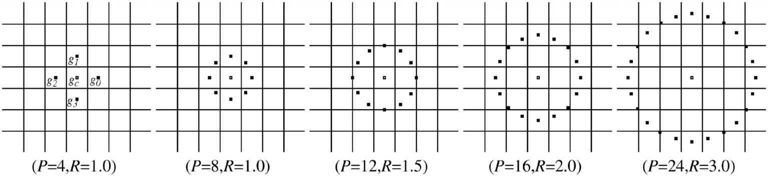


Figure 5: Circularly symmetric sampling patterns for different (P, R) configurations [1].

Rotation-Invariant LBP

- Standard LBP depends on neighbor ordering.
- Rotation invariance is achieved by finding the **minimum decimal value** over all circular bitwise rotations:

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

  where ROR = circular right shift.

- This ensures that rotated microstructures produce identical LBP codes.

Example:
A pattern like:

$$10000111 \rightarrow 00001111 \rightarrow 00011110 \rightarrow \ldots$$

Choose the smallest decimal value among all rotations.

Uniform LBP and RIU2 Mapping

- **Uniform patterns**: binary patterns with at most two bitwise transitions (0→1 or 1→0) when traversed circularly.

$$U(\mathrm{LBP}) = |b_{P-1} - b_0| + \sum_{p=1}^{P-1} |b_p - b_{p-1}|$$

- Patterns with $U(\mathrm{LBP}) \leq 2$ are called **uniform**.
- More than 90% of local patterns in natural images are uniform patterns.

RIU2 Mapping:

$$\mathrm{LBP}_{P,R}^{riu2} = \begin{cases} \sum b_p, & U(\mathrm{LBP}) \leq 2 \\ P+1, & \text{otherwise} \end{cases}$$

- Output histogram size reduces from 2^P to $P+2$ bins.
- This greatly reduces dimensionality while preserving discriminative power.

Local Variance (VAR) and Nonparametric Classification

- LBP captures **structure**, but ignores **local contrast**.
- Ojala et al.[1] propose the variance (VAR) as a complementary descriptor. For each pixel, VAR is computed over the same circular neighborhood:

$$VAR_{P,R}(x_c) = \frac{1}{P}\sum_{p=0}^{P-1}(g_p - \mu)^2, \quad \mu = \frac{1}{P}\sum_{p=0}^{P-1} g_p$$

Nonparametric Classification Principle

- Each texture class is represented by a **model histogram** built from training samples.
- A test image produces a histogram S, which is compared to each class histogram M.
- Classification is done by maximizing the log-likelihood similarity:

$$\mathrm{Score}(S, M) = \sum_i S(i) \log(M(i))$$

LBP: Pseudo-code (per pixel)

for each pixel c **do**
    $g_c \leftarrow$ intensity at pixel c
    for $p = 0$ to $P - 1$ **do**
        compute (y_p, x_p) on circle of radius R
        $g_p \leftarrow \text{bilinear\_interpolate}(\text{image}, y_p, x_p)$
        $bit_p \leftarrow \begin{cases} 1 & \text{if } g_p \geq g_c \\ 0 & \text{otherwise} \end{cases}$
    end for
    $LBP \leftarrow \sum_{p=0}^{P-1} bit_p \cdot 2^p$
    if rotation invariant **then**
        $LBP \leftarrow \text{min\_rotate}(LBP)$
    end if
    if RIU2 mapping enabled **then**
        $u \leftarrow \text{uniformity}(LBP)$
        if $u \leq 2$ **then**
            output $\leftarrow \text{popcount}(LBP)$
        else
            output $\leftarrow P + 1$
        end if
    end if
end for

Dataset: Brodatz Rotated Textures (USC-SIPI)

- We use only the **rotated texture subset** from `rotate.zip` of the USC-SIPI texture database.
- This subset contains **13 Brodatz textures**, each digitized at $0^\circ, 30^\circ, 60^\circ, 90^\circ, 120^\circ, 150^\circ, 200^\circ$, resulting in a total of **91 images**.
- The 13 textures used are: `bark`, `brick`, `bubbles`, `grass`, `leather`, `pigskin`, `raffia`, `sand`, `straw`, `water`, `weave`, `wood`, `wool` (example shown in Fig. 1).
- **Experimental protocol:** For each texture class, the model is trained using *one* rotation angle and tested on the remaining six rotated versions.
- All images are **grayscale, 512×512, 8-bit**. They were digitized using a video camera, so the quality is slightly lower than the original unrotated Brodatz images.

Implementation Details

- **Patch extraction (16×16 subimages):** Each 512×512 texture is divided into fixed 16×16 patches to increase training samples and capture local texture statistics.
- **Lookup tables (LUTs):** Precomputed LUTs map raw LBP codes to RIU2 labels, uniformity values, rotation-min codes, and popcount, avoiding expensive per-pixel recomputation.
- **Bilinear interpolation:** Neighbor pixel values on the circular sampling ring are estimated using custom bilinear interpolation for non-integer coordinates.
- **VAR quantization:** Local variance values are discretized into bins using cut-points computed from training statistics.
- **Numerical stability:** Histogram models use Laplace smoothing and log-probabilities during classification to prevent zero-probability errors and floating-point underflow.

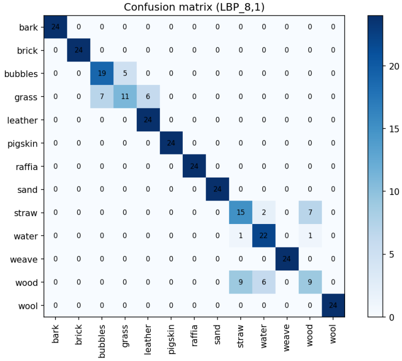
Accuracy results (summary)

Operator	Train 0	Train 30	Train 60	Train 90	Avg
LBP_8,1	88.46%	89.74%	84.62%	83.33%	86.54%
LBP_16,2	93.59%	96.15%	94.87%	94.87%	94.87%
LBP_24,3	100.00%	98.72%	100.00%	100.00%	99.68%
LBP_16,2/VAR	100.00%	100.00%	100.00%	100.00%	100.00%
LBP_24,3/VAR	98.72%	100.00%	100.00%	100.00%	99.68%
LBP_8,1+16,2	92.31%	93.59%	87.18%	92.31%	91.35%

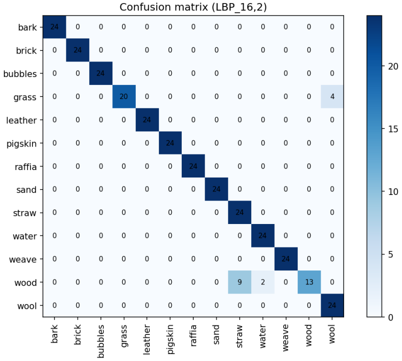
Table 1: Performance of operators at four different training angles

- Best results achieved by combined multi-resolution (16,2 or 24,3) operators and when using VAR combined with LBP.
- RIU2 reduces descriptor dimensionality and preserves rotation invariance.

Confusion Matrices

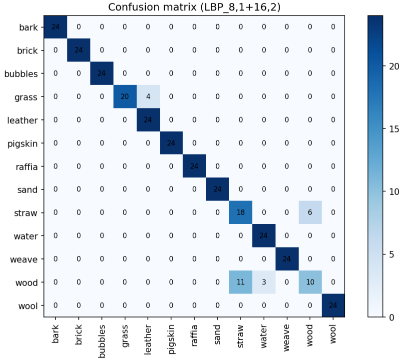


$LBP_{8,1}$

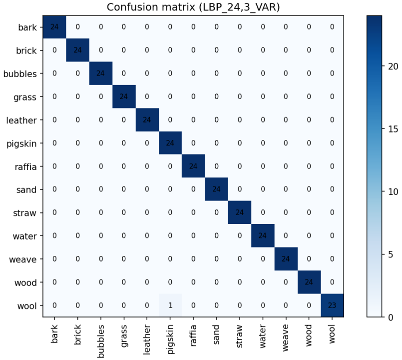


$LBP_{16,2}$

Confusion Matrices



$\mathrm{LBP}_{8,1} + \mathrm{LBP}_{16,2}$

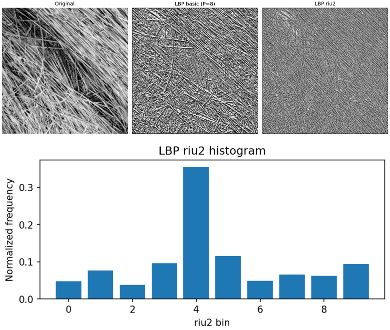


$\mathrm{LBP}_{24,3} + \mathrm{VAR}$

Why Wood and Straw are Confused (LBP_8,1)

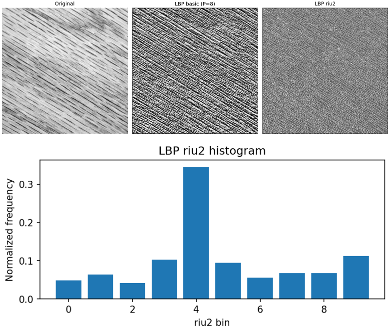
Both **wood** and **straw** exhibit strong directional, line-like textures. With small-radius LBP ($P = 8, R = 1$), many local neighborhoods become similar: parallel edges produce nearly identical LBP riu2 histograms, leading to confusion.

Straw texture



LBP map and riu2 histogram (Straw)

Wood texture



LBP map and riu2 histogram (Wood)

Observation: Both textures produce very similar dominant riu2 bins due to repeated linear micro-patterns.

Conclusions

- Multi-resolution LBP (especially $P = 16, R = 2$ and $P = 24, R = 3$) provides strong rotation-invariant discrimination on the Brodatz rotated texture set.
- Increasing P and R improves accuracy because larger neighborhoods capture texture structures at coarser spatial scales, making the descriptor more sensitive to dominant orientation patterns and long-range correlations rather than just fine local noise.
- Adding local variance (VAR) complements LBP by encoding contrast information that pure binary patterns discard, leading to substantially better class separation.
- The combined use of multi-scale neighborhood structure and local contrast yields a robust and compact representation for rotated texture classification.

References

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