Texture analysis with local binary patterns

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Outline

Introduction

LBP methodology

Overview of some recent work

New results

- LBP in facial image analysis
- LBP in detecting moving objects

Conclusions

Introduction

Motivation

2-D surface texture is a valuable cue in machine vision

➔ to develop leading-edge methodology for 2-D texture analysis

➔ to create basis for new applications of machine vision

Guiding principles

➔ computational simplicity for real-time operation

➔ invarinace wrt. illumination changes

➔ invariance wrt. spatial rotation of objects

Starting point

2-D surface texture is a two dimensional phenomenon characterized by:

- spatial structure (pattern)
- contrast ('amount' of texture)

Transformation	Property: Pattern	Property: Contrast
Gray scale	no effect	affects
Rotation	affects	no effect
Zoom in/out	affects	?

Thus,

1) contrast is of no interest in gray scale invariant analysis
2) often we need a gray scale and rotation invariant pattern measure

LBP/C: Local Binary Pattern and Contrast operator

Reference: Ojala T, Pietikäinen M & Harwood D (1996) A comparative study of texture measures with classification based on feature distributions. Pattern Recognition 29:51-59.

Joint occurrences of LBP and Contrast are considered

An example of computing LBP and C in a 3x3 neighborhood:

example

6	5	2
7	6	1
9	8	7

thresholded

1	0	0
1		0
1	1	1

weights

1	2	4
128		8
64	32	16

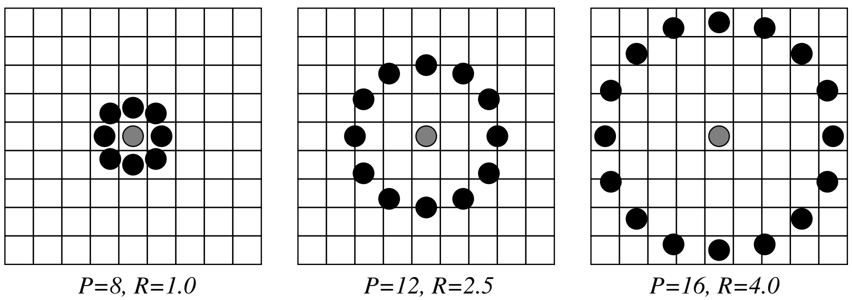
Pattern = **11110001**

LBP = 1 + 16 +32 + 64 + 128 = **241**

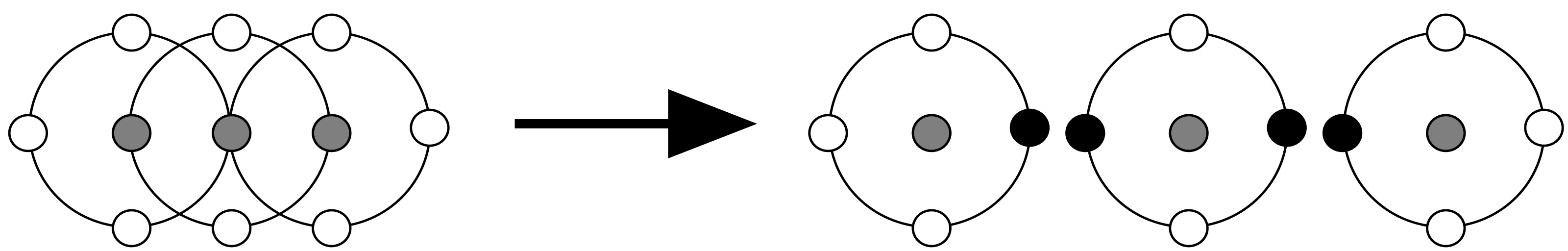
C = (6+7+8+9+7)/5 - (5+2+1)/3 = **4.7**

Circurlarly symmetric neighbtbor sets

Reference: Ojala T, Pietikäinen M & Mäenpää T (2002) Multiresolution gray-scale and rotation invariant texture classification with Local Binary Patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence 24(7):971-987.

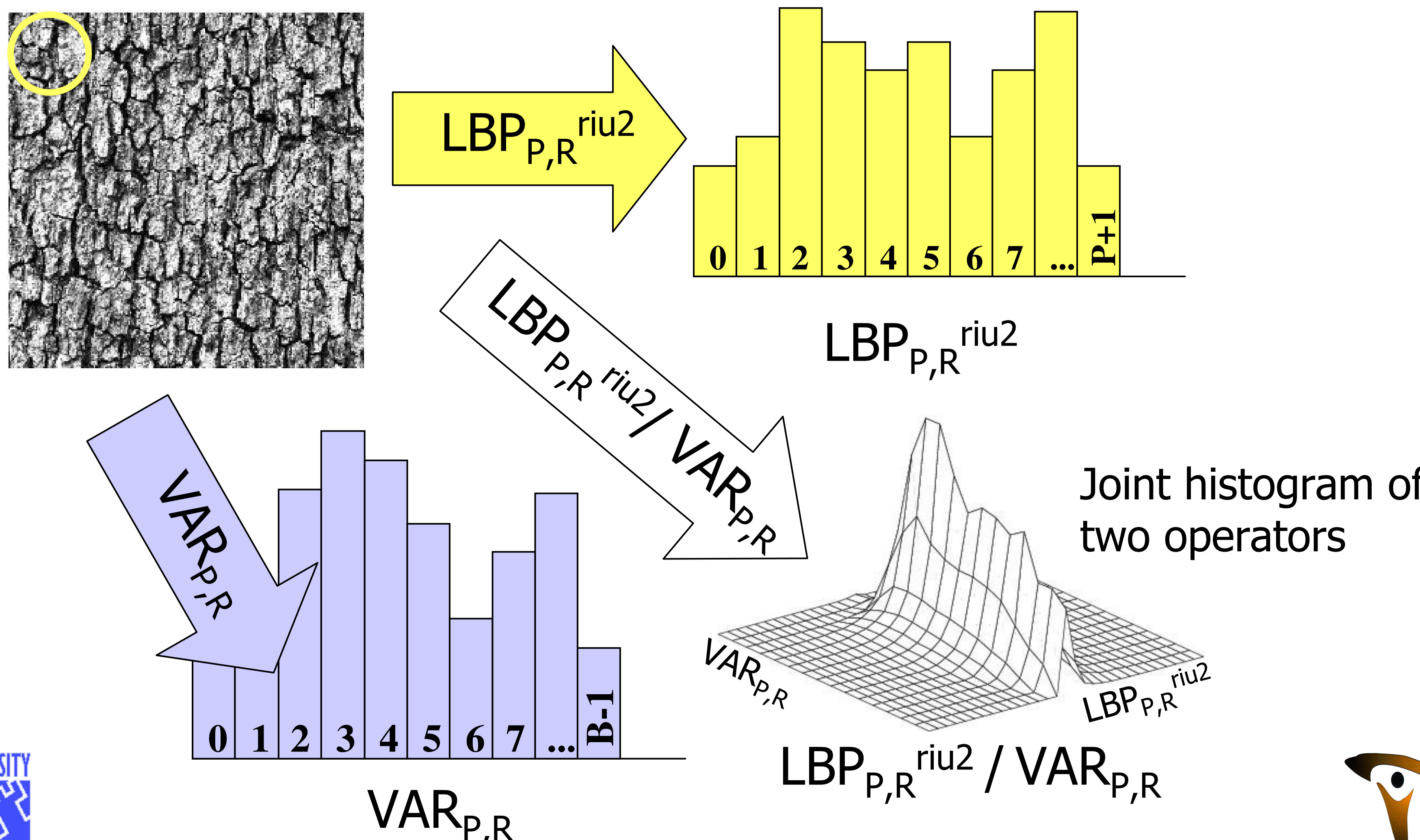


Three adjacent $LBP_{4,R}$ neighborhoods and an impossible combi-nation of codes. A black disk means the gray level of a sample is lower than that of the center.

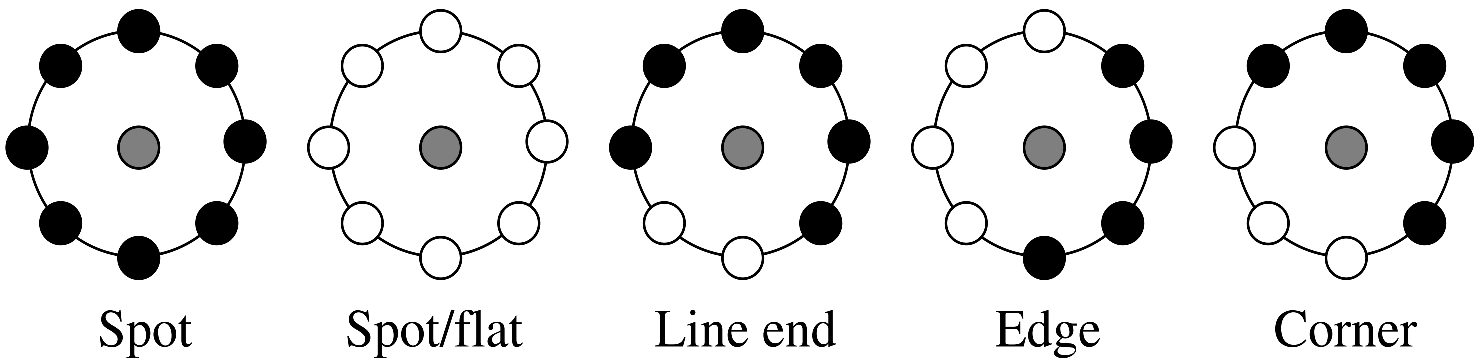


Estimation of empirical feature distributions

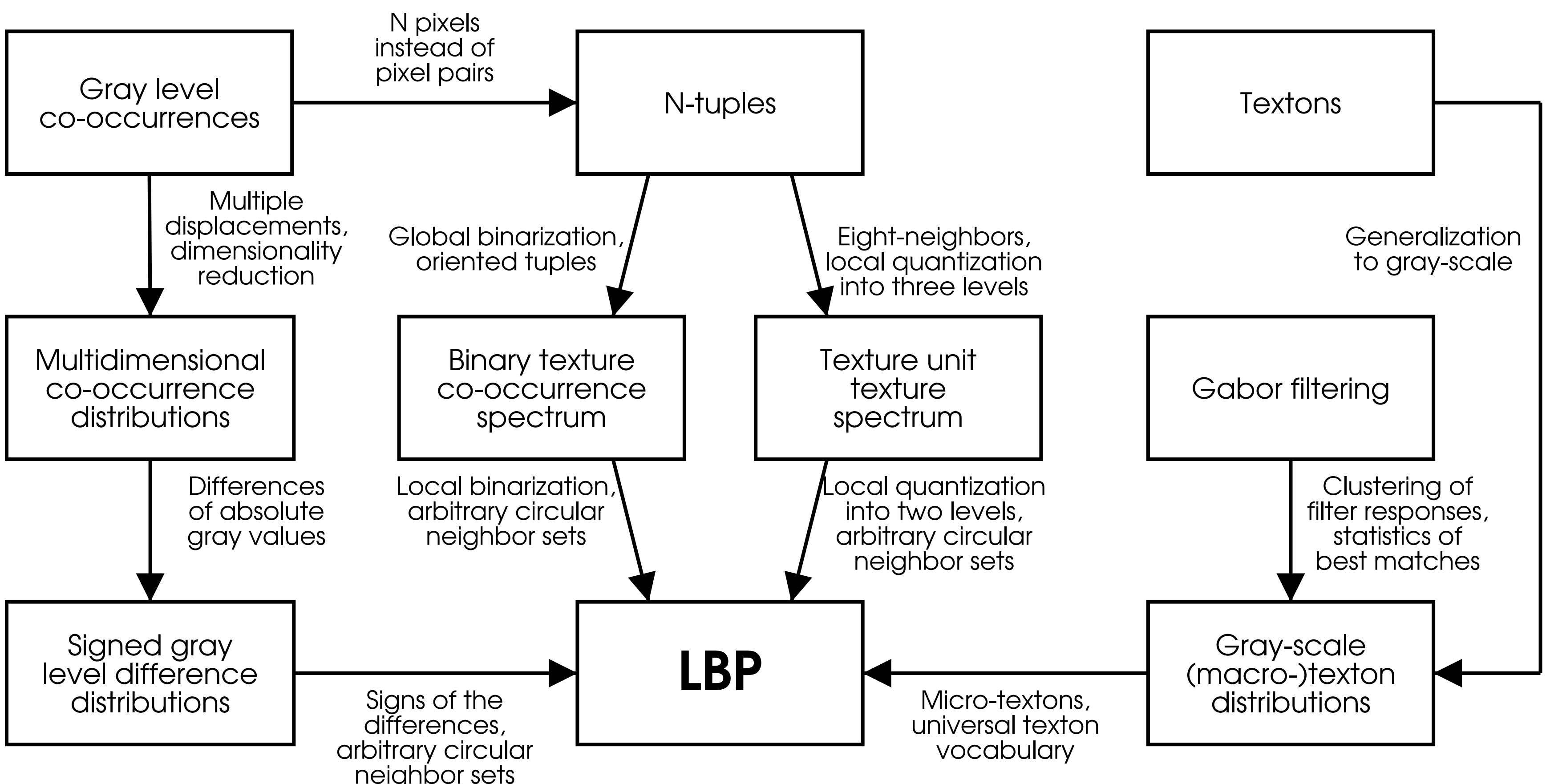
Input image is scanned with the chosen operator(s), pixel by pixel, and operator outputs are accumulated into a discrete histogram



Texture primitives detected by the LBP



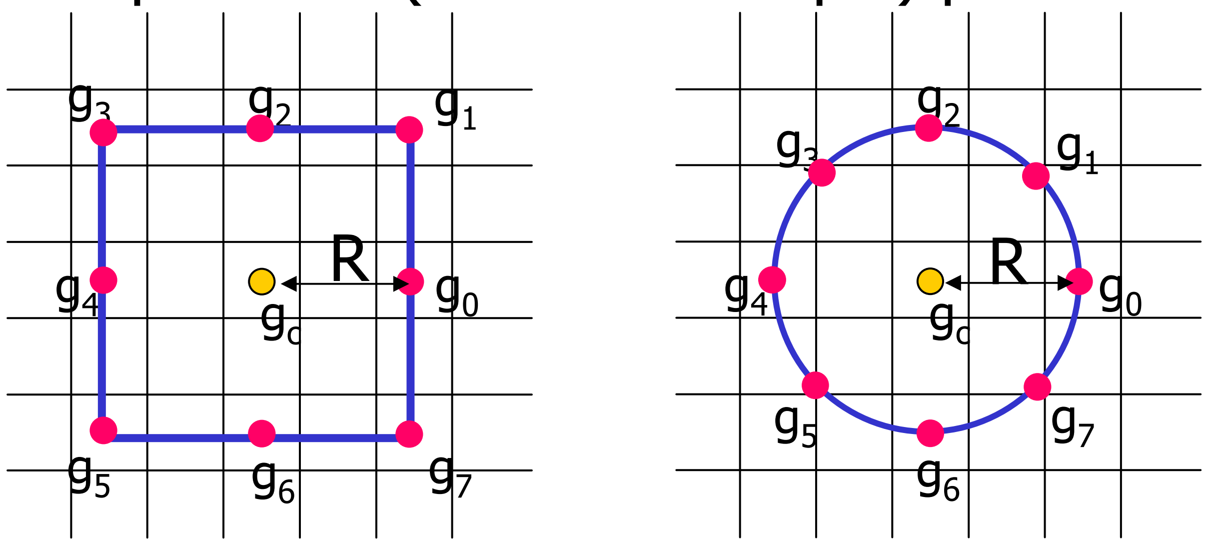
LBP in the field of texture operators



LBP methodology

Description of local image texture

Texture at g_c is modeled using a local neighborhood of radius R, which is sampled at P (8 in the example) points:



Square neighborhood

Circular neighborhood (g_1,g_3,g_5,g_7 interpolated)

Let's define texture T as the joint distribution of gray levels g_c and g_p (p=0,…, P-1):

$$T = t(g_c, g_0, \ldots, g_{P-1})$$

Description of local image texture (cont.)

Without losing information, we can subtract g_c from g_p:

$$T = t(g_c, g_0 - g_c, \ldots, g_{P-1} - g_c)$$

Assuming g_c is independent of g_p-g_c, we can factorize above:

$$T \sim t(g_c)\, t(g_0-g_c, \ldots, g_{P-1}-g_c)$$

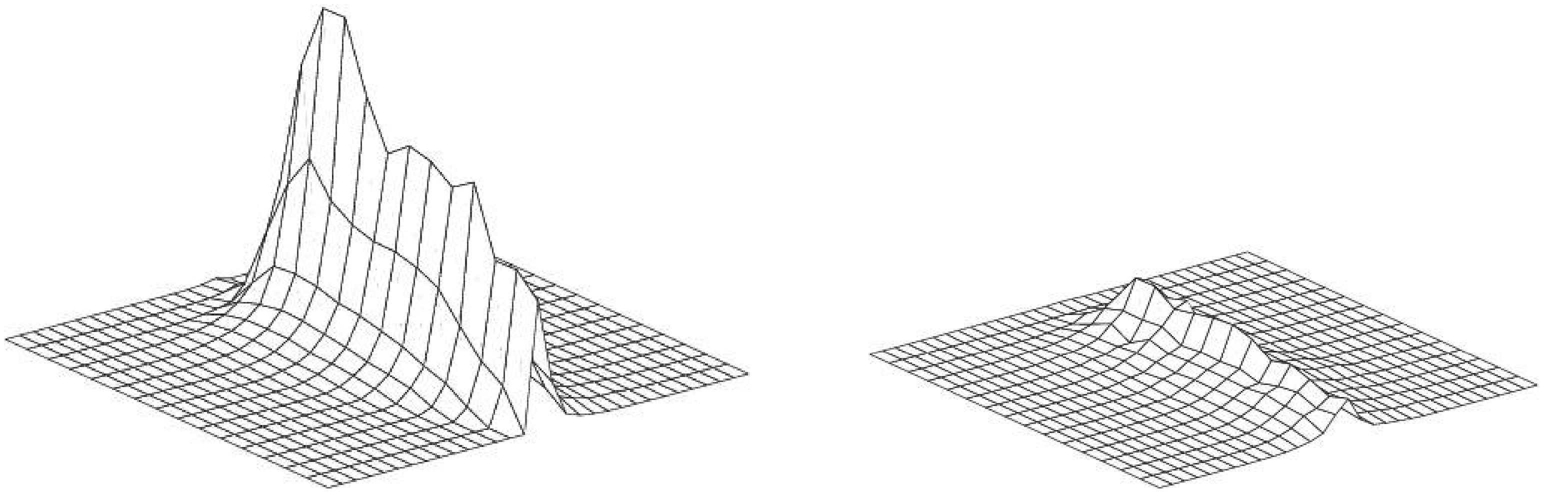
$t(g_c)$ describes the overall luminance of the image, which is unrelated to local image texture, hence we ignore it:

$$T \sim t(g_0-g_c, \ldots, g_{P-1}-g_c)$$

Above expression is invariant wrt. gray scale shifts

Description of local image texture (cont.)

Exact independence of $t(g_c)$ and $t(g_0-g_c, \ldots, g_{P-1}-g_c)$ is not warranted in practice:



average $t(g_c,g_0- g_c)$ average absolute difference between $t(g_c,g_0- g_c)$ and $t(g_c)\, t(g_0-g_c)$

Pooled (G=16) from 32 Brodatz textures used in
Ojala, Valkealahti, Oja & Pietikäinen (Pattern Recognition 34, 2001)

Signed gray level differences

Reference: Ojala T, Valkealahti K, Oja E & Pietikäinen M (2001) Texture discrimination with multidimensional distributions of signed gray level differences. Pattern Recognition 34:727-739.

Cooccurring differences provide more information than just one. Computing cooccurring differences in 3x3 subimages:

g_3	g_2	g_1
g_4	g_c	g_0
g_5	g_6	g_7

we estimate distributions

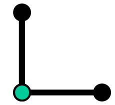
$p_2\,(g_0-g_c, g_2-g_c)$

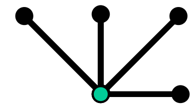
$p_4\,(g_0-g_c, g_1-g_c, g_2-g_c, g_3-g_c)$

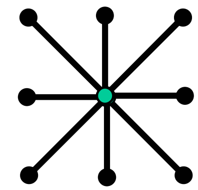
$p_8\,(g_0-g_c, g_1-g_c, \ldots, g_7-g_c)$

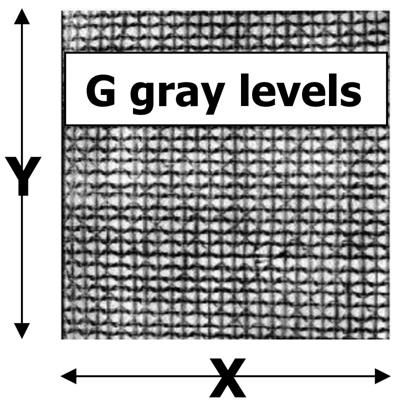
Signed gray level differences (cont.)

1	2	5
7	5	8
9	3	6

$p_2 = (3,-3)$ 

$p_4 = (3,-3,0,-4)$ 

$p_8 = (3,-3,0,-4,2,4,-2,1)$ 



⇒ $(Y-2)(X-2)$ difference vectors

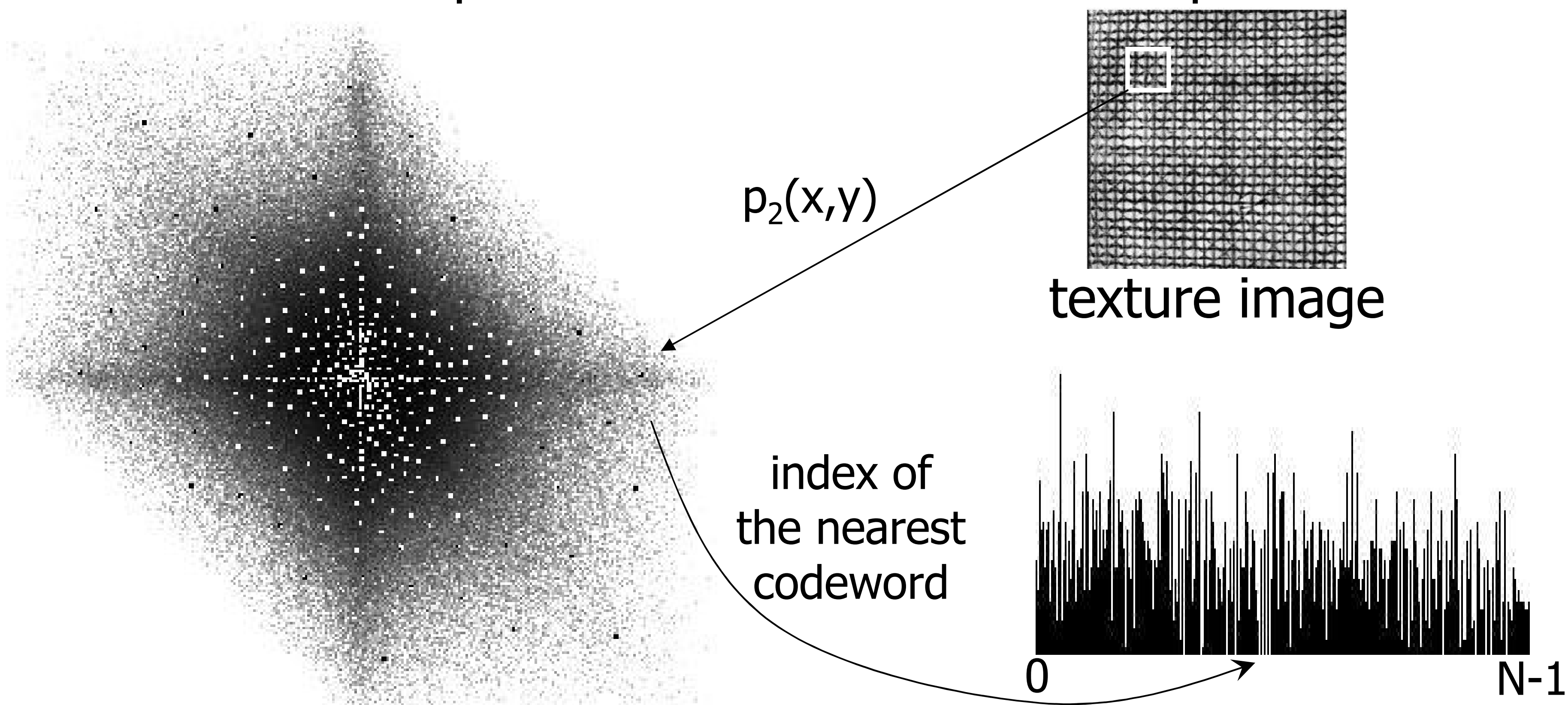
p_k $(k=2,4,8)$ estimated with a discrete histogram of N bins

Stability criterion: $f_{ave} = (Y-2)(X-2)/N \geq f_{min}$ (~ 5 or 10)

Volume of the difference space: $V = (2G-1)^k >> N$

Signed gray level differences (cont.)

Vector quantization of the difference space



difference space of p_2 quantized with a codebook of N codewords

$N \sim (X-2)(Y-2)/f_{min}$

discrete histogram estimating p_2

LBP: Local Binary Pattern

Reference: Ojala T, Pietikäinen M & Harwood D (1996) A comparative study of texture measures with classification based on feature distributions. Pattern Recognition 29:51-59.

Invariance wrt. any monotonic transformation of the gray scale is achieved by considering the signs of the differences:

$$T \sim t(s(g_0-g_c), \ldots, s(g_{P-1}-g_c))$$

where

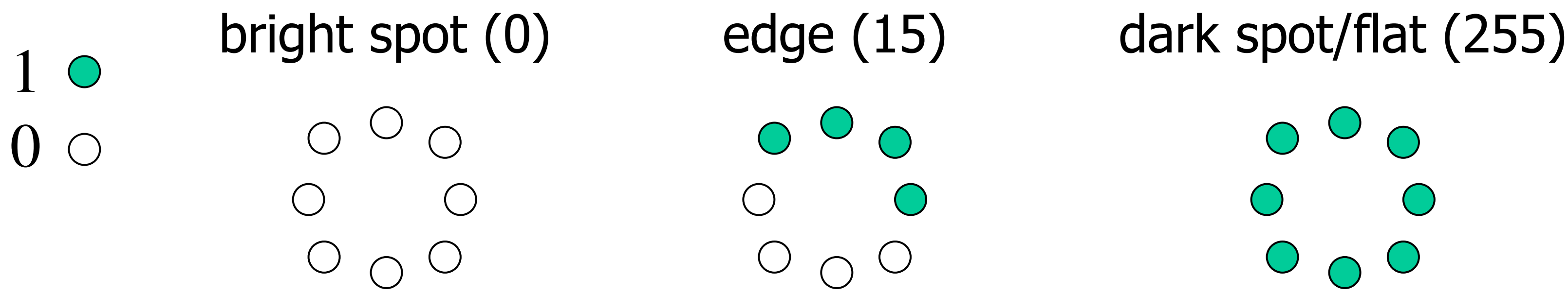
$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

Above is transformed into a unique P-bit pattern code by assigning binomial coefficient 2^p to each sign $s(g_p-g_c)$:

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

LBP: Local Binary Pattern (cont.)

$LBP_{P,R}$ encodes simple binary microstructures into a P-bit number:

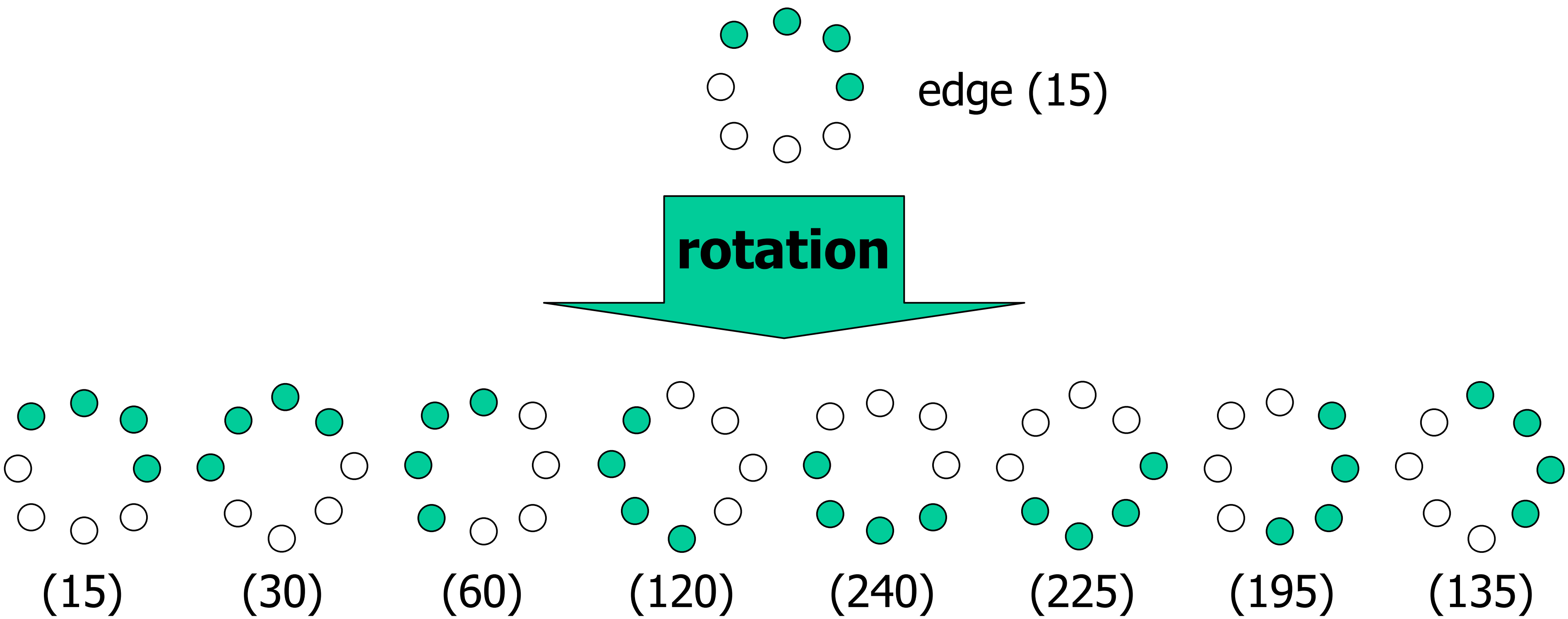


$LBP_{8,R}$ provides less information than signed difference p_8, but
+ invariant wrt. any monotonic transformation of the gray scale
+ vector quantization not needed
+ computational simplicity

Rotation invariant LBP

Reference: Pietikäinen M, Ojala T & Xu Z (2000) Rotation-invariant texture classification using feature distributions. Pattern Recognition 33:43-52.

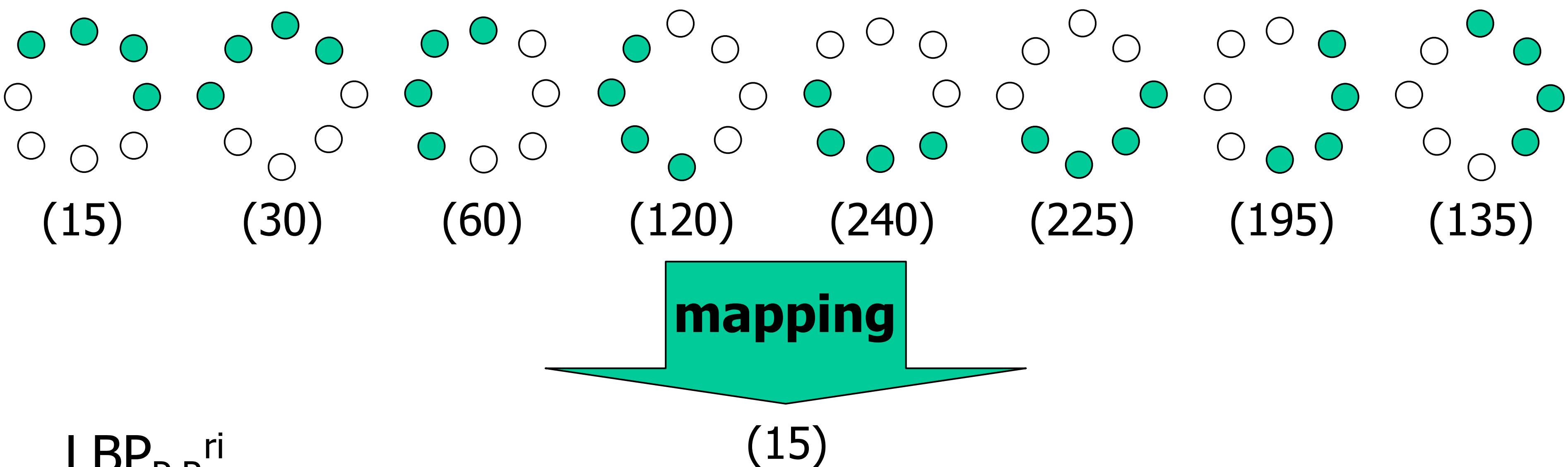
Spatial rotation of the binary pattern changes the LBP code:



Rotation invariant LBP (cont.)

Formally, rotation invariance can be achieved by defining:

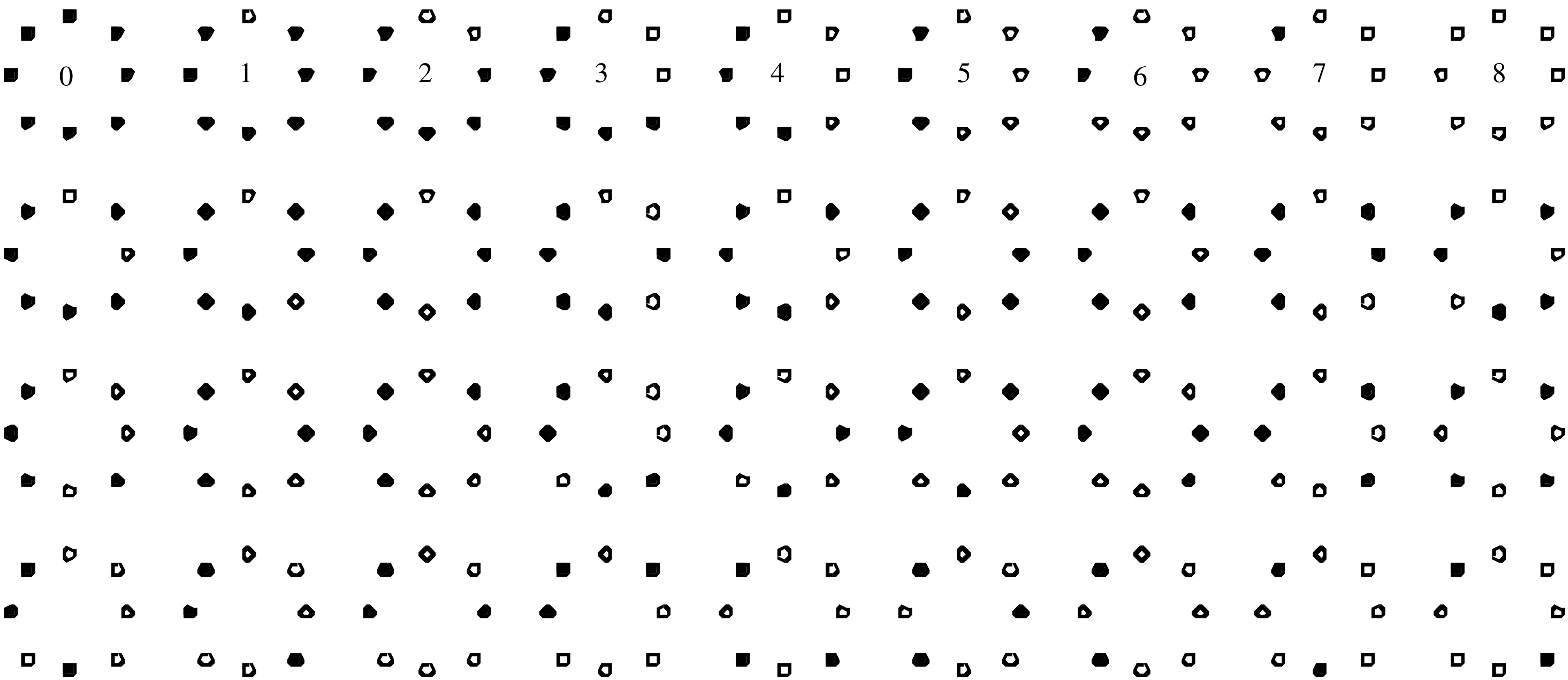
$$LBP_{P,R}^{ri} = \min\{ROR(LBP_{P,R}, i) \mid i=0, \ldots, P-1\}$$



$LBP_{P,R}^{ri}$

- invariant wrt. any monotonic gray scale transformation
- invariant wrt. rotation along the circular neighborhood

Rotation invariant LBP (cont.)



36 rotation invariant patterns encoded in $LBP_{8,R}^{ri}$

Rotation invariant LBP (cont.)

However, $LBP_{8,1}^{ri}$ provides poor performance:

• crude quantization of the angular space at 45° intervals
➔ finer quantization by larger P, e.g. 16 (22.5°) or 24 (15°)

• all 36 rotation invariant patterns are not equally useful
➔ use a subset of so-called ‘uniform’ patterns

'Uniform' patterns

Reference: Ojala T, Pietikäinen M & Mäenpää T (2002) Multiresolution gray-scale and rotation invariant texture classification with Local Binary Patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence 24(7):971-987.

Heuristic hypothesis

Certain local binary patterns are fundamental properties of texture, providing a vast majority, sometimes over 90%, of all 3x3 patterns in the observed textures

➔ define the concept of 'uniform' patterns, which have a limited number of spatial transitions

➔ use only 'uniform' patterns

➔ exclude 'nonuniform' patterns of high angular frequency (they provide statistically unreliable information)

'Uniform' patterns (cont.)

Pattern 'uniformity' measure $U(LBP_{P,R}^{ri})$:

$$U(LBP_{P,R}) = |s(g_{P-1}-g_c) - s(g_0-g_c)| + \sum_{p=1}^{P-1} |s(g_p-g_c) - s(g_{p-1}-g_c)|$$

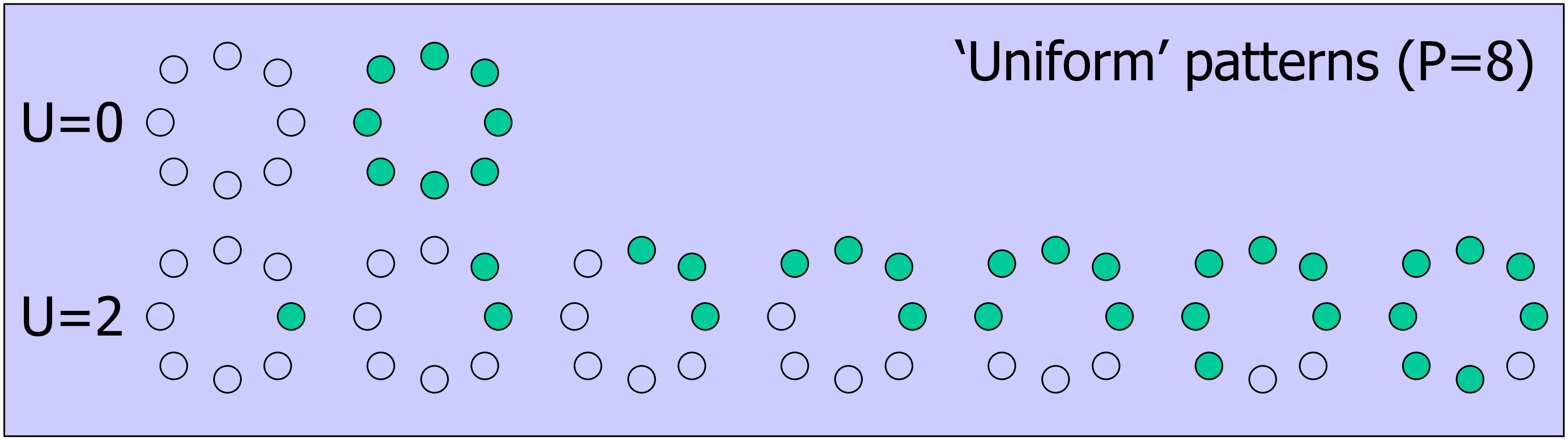
$U(LBP_{P,R})$ ~ # bitwise 0/1 transitions in the circular bit pattern

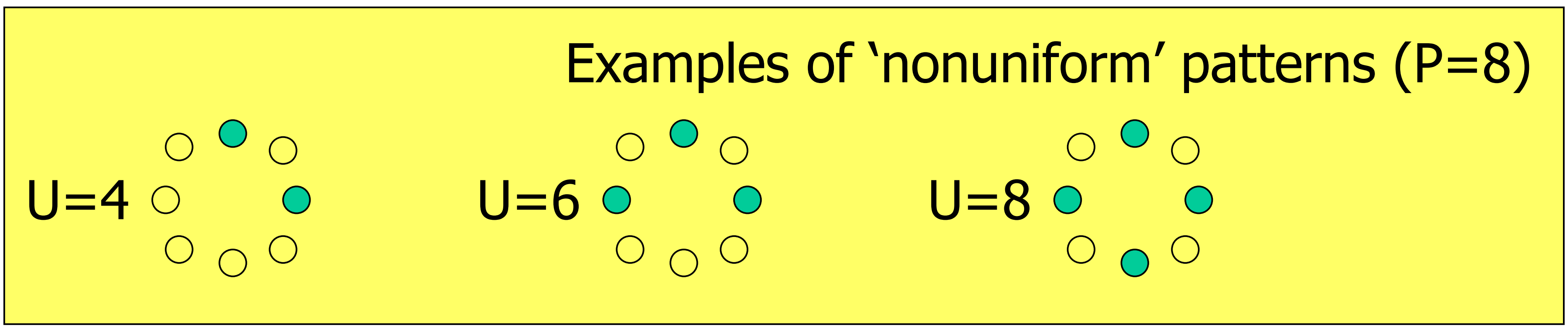
Pattern is considered 'uniform', if $U(LBP_{P,R}) <= 2$

i.e. pattern has at most 1 bitwise spatial transition

'Uniform' patterns seem to dominate in deterministic Brodatz-like textures!

‘Uniform’ patterns (cont.)





‘Uniform’ patterns (cont.)

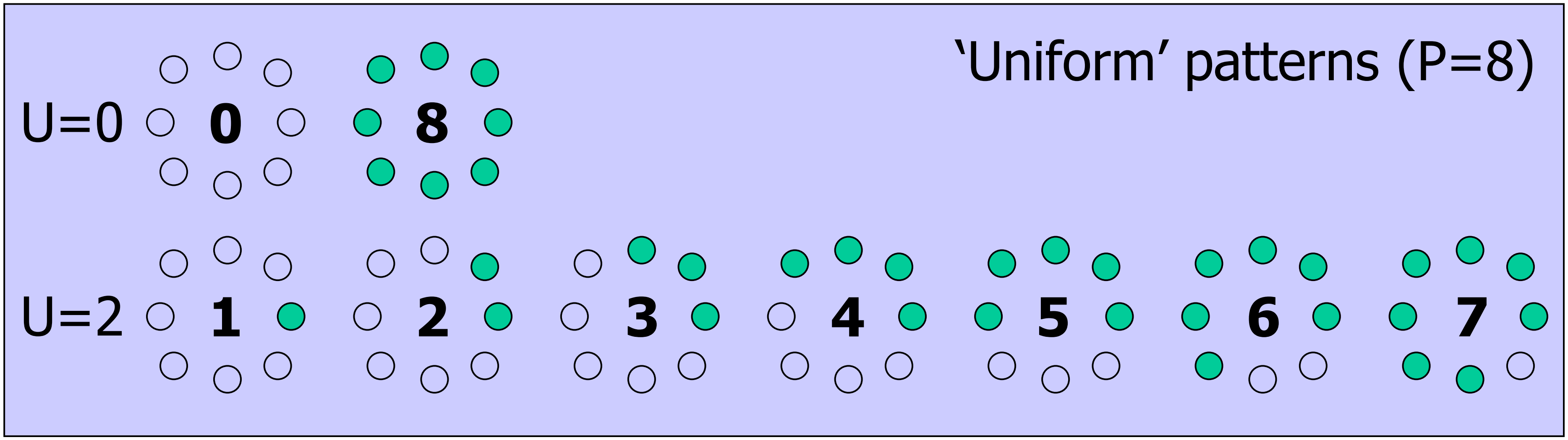
Gray scale and rotation invariant operator based on ‘uniform’ Local Binary Patterns:

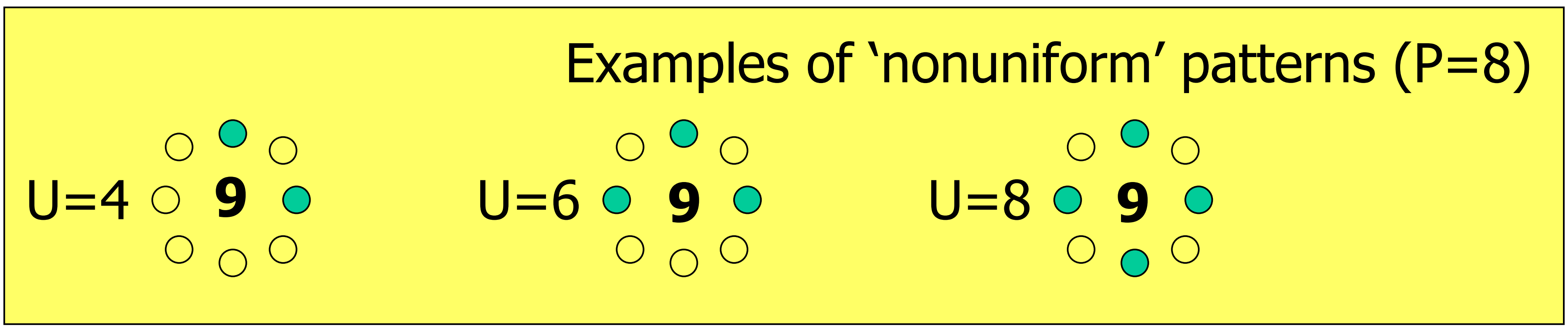
$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{P-1} s\,(g_p - g_c) & \text{if } U(LBP_{P,R}) <= 2 \\ P+1 & \text{otherwise} \end{cases}$$

$LBP_{P,R}^{riu2}$ ~ # ‘1’ bits if ‘uniform’ pattern, otherwise P+1

efficient implementation with a lookup table

‘Uniform’ patterns (cont.)





Operators for characterizing texture contrast

Center-symmetric variance measure:

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

where

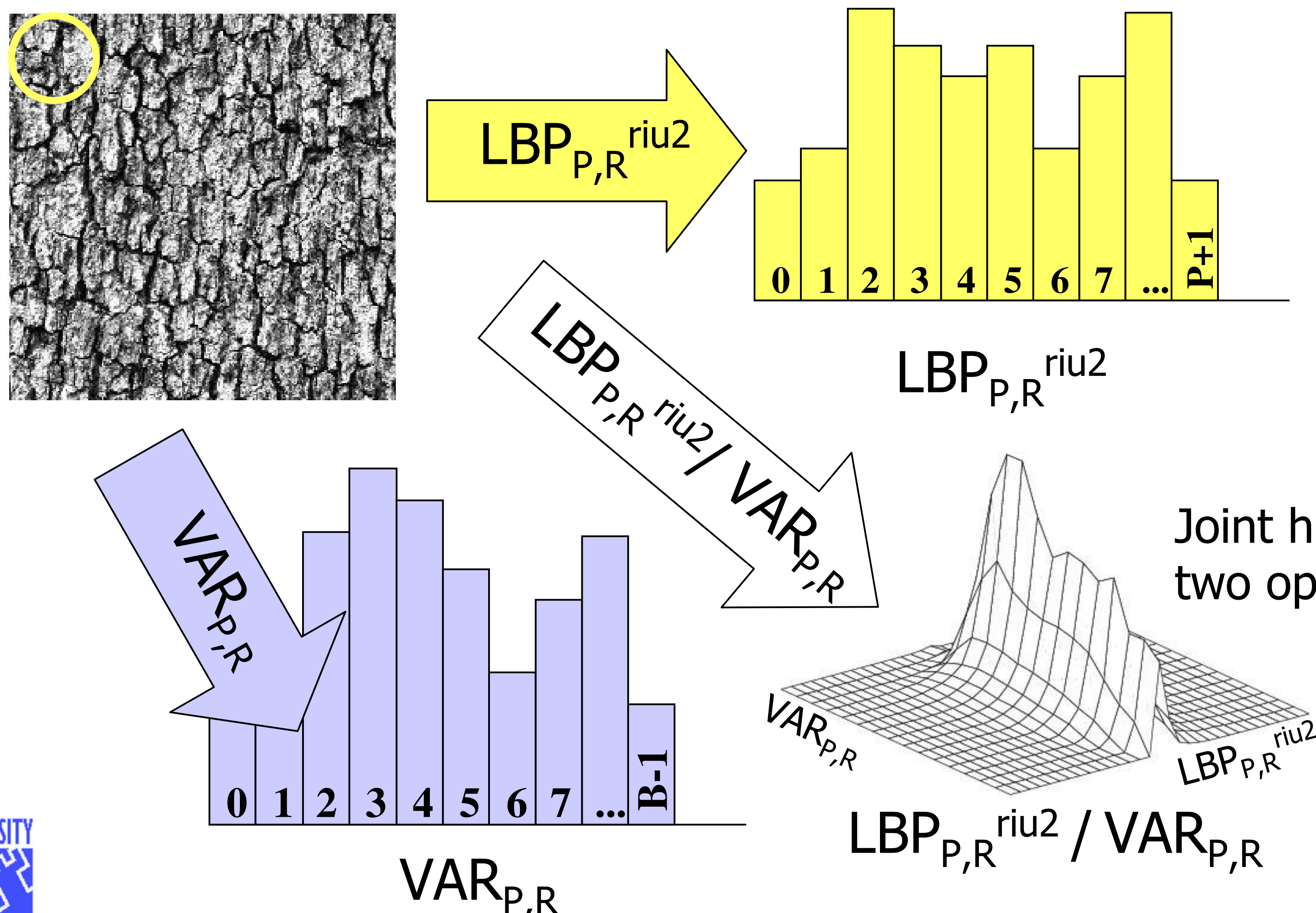
$$\mu = \frac{1}{P} \sum_{p=0}^{P-1} g_p$$

$VAR_{P,R}$

- invariant wrt. gray scale shifts
- invariant wrt. rotation along the circular neighborhood

Estimation of empirical feature distributions

Input image is scanned with the chosen operator(s), pixel by pixel, and operator outputs are accumulated into a discrete histogram



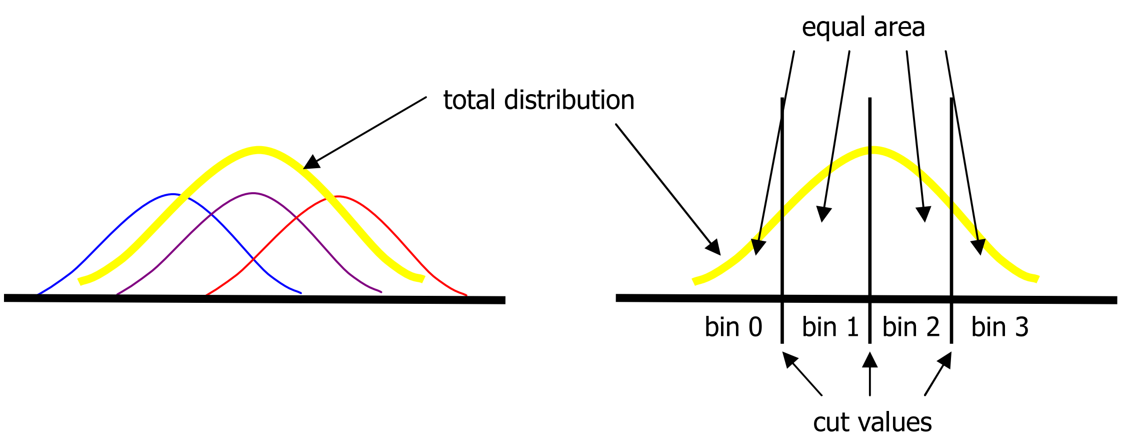
Quantization of continuous feature space

Texture statistics are described with discrete histograms

- Mapping needed for continuous-valued features

Nonuniform quantization

- Every bin have the same amount of total data
- Highest resolution of the quantization is used where the number of entries is largest



Nonparametric classification principle

Sample S is assigned to the class of model M that maximizes

$$L(S,M) = \sum_{b=0}^{B-1} S_b \ln M_b$$

Many other dissimilarity measures can be used (chi square, Kullback-Leibler divergence, Jeffrey's divergence, etc.)

Nonparametric: no assumptions about underlying feature distributions are made!!

Multichannel/multiresolution analysis

Reference: Ojala T & Pietikäinen M (1998) Nonparametric multichannel texture description with simple spatial operators. Proc. 14th International Conference on Pattern Recognition, Brisbane, Australia, 1052-1056.

Information provided by N operators can be combined simply by summing up operator wise similarity scores into an aggregate similarity score:

$$L_N = \sum_{n=1}^{N} L_n$$

Effectively, the above assumes that distributions of individual operators are independent

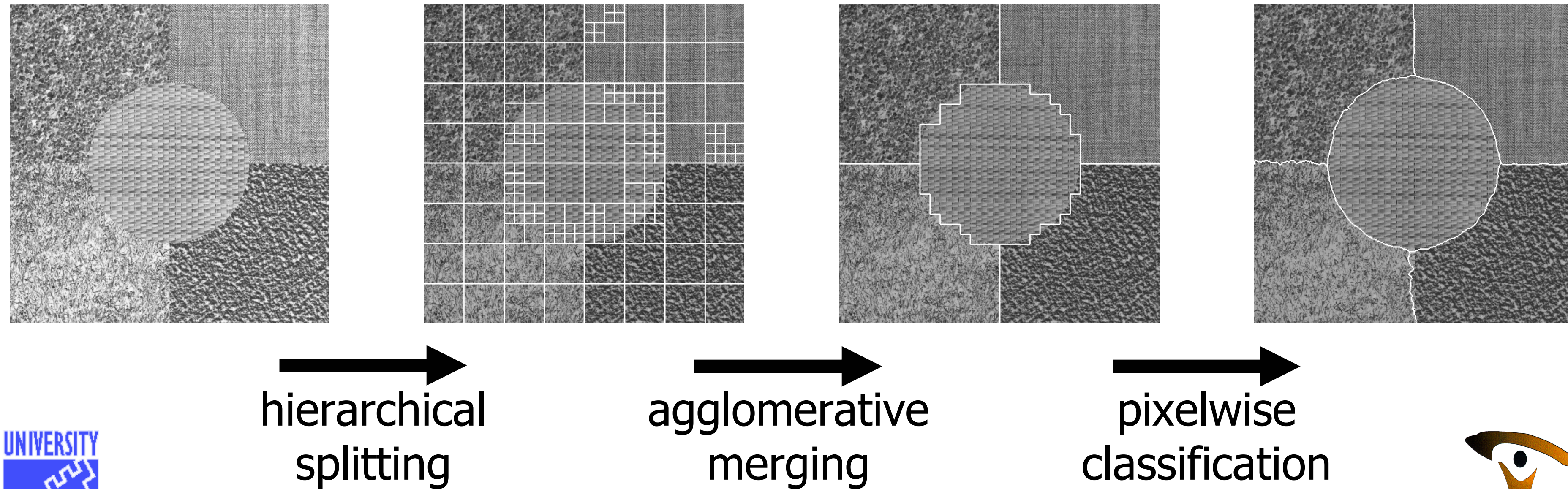
Unsupervised texture segmentation

Reference: Ojala T & Pietikäinen M (1999) Unsupervised texture segmentation using feature distributions. Pattern Recognition 32:477-486.

- LBP/C was used as texture operator

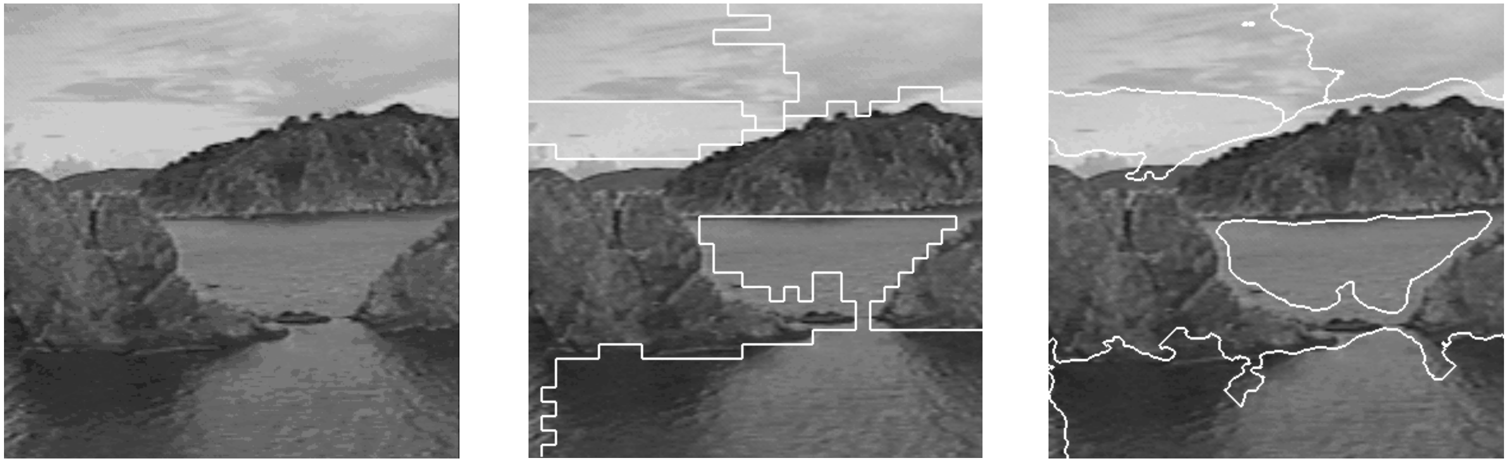
Segmentation algorithm consists of three phases:

1. hierarchical splitting
2. agglomerative merging
3. pixelwise classification

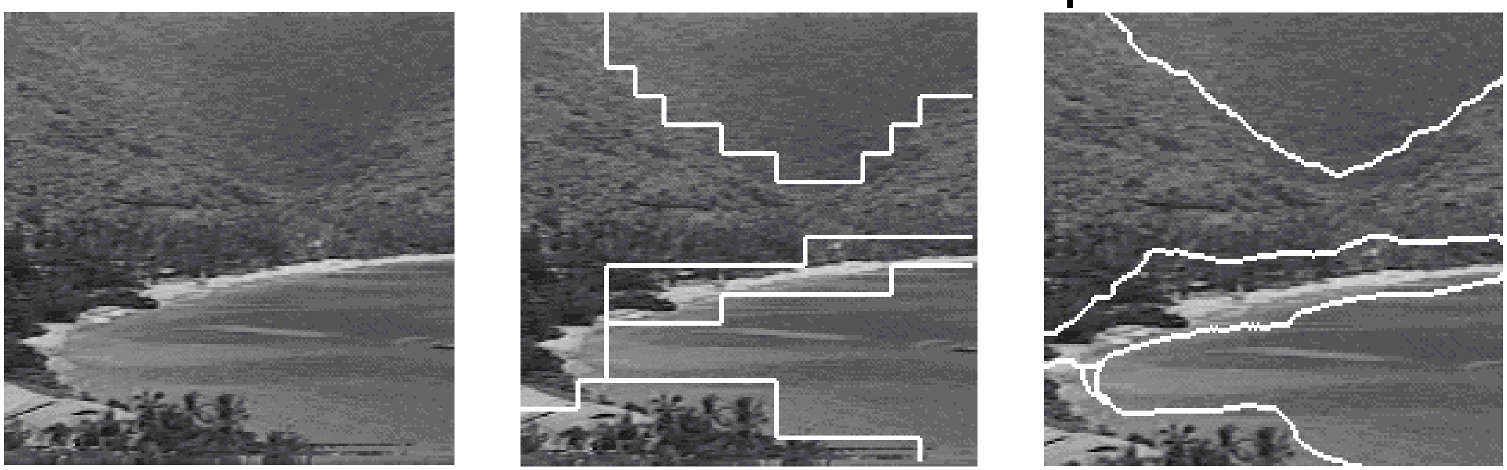


Experiment in unsupervised texture segmentation

Natural scene #1: 384x384 pixels



Natural scene #2: 192x192 pixels



Overview of some recent work

- Outex - a framework for empirical evaluation of texture analysis algorithms
- color texture classification
- multiscale extensions of LBP
- view-based recognition of 3D-textured surfaces
- visual training for scene classification
- application studies:
  - wood inspection
  - paper characterization
  - real-time processing
  - empirical evaluation of MPEG-7 texture descriptors
- C++ libraries
- general references to LBP

Outex

Reference: Ojala T, Mäenpää T, Pietikäinen M, Viertola J, Kyllönen J & Huovinen S (2002) Outex - New framework for empirical evaluation of texture analysis algorithms. Proc. 16th International Conference on Pattern Recognition, Quebec, Canada, 1:701-706.

A new test database available at http://www.outex.oulu.fi

1. 319 color textures captured using three different illuminants
2. six spatial resolutions and nine rotation angles
3. test suites for texture classification, texture retrieval, supervised segmentation, unsupervised segmentation

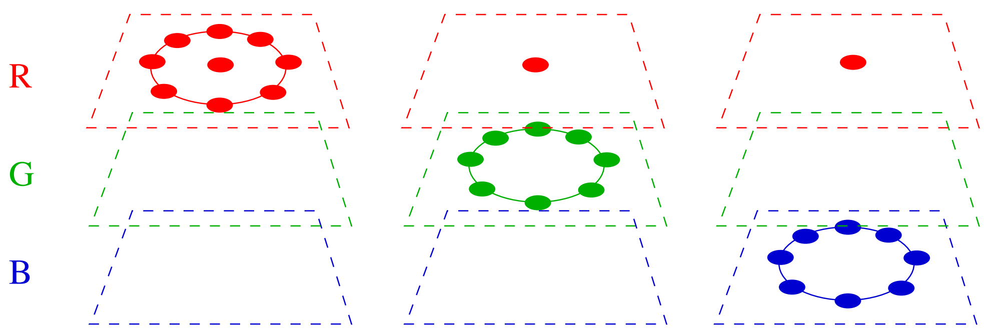
4. a collection of scene textures

Color texture classification

Reference: Mäenpää T & Pietikäinen M (2004) Classification with color and texture: jointly or separately? Pattern Recognition 37(8):1629-1640.

- experiments with VisTex and Outex color textures
- color histograms, color texture operators, gray-scale texture operators
- combining separate color and texture features
- the results indicate that color and texture can, or even should, be treated individually
- color histograms performed best in static illumination conditions
- LBP texture features performed best under varying illumination

Creating opponent color LBP codes



Color texture classification (cont.)

Reference: Mäenpää T, Viertola J & Pietikäinen M (2002) Optimising colour and texture features for real-time visual inspection. Pattern Analysis and Applications 6(3):169-175.

- a method for optimizing color and texture features is proposed for obtaining good performance and real-time operation
- color percentile features, LBP, and edge-based texture features are used in examples
- a parquet defect classification problem is used as a case study

Multi-scale extensions of LBP

Reference: Mäenpää T & Pietikäinen M (2003) Multi-scale binary patterns for texture analysis. Proc. 13th Scandinavian Conference on Image Analysis (SCIA 2003), June 29 - July 2, Göteborg, Sweden, 885-892.

- presents two novel ways of extending the LBP to multiple scales
- a method using Gaussian low-pass filtering is somewhat helpful, but too slow
- a very promising method based on cellular automata is proposed as a way of compactly encoding arbitrarily large circular neighborhoods

View-based recognition of 3D-textured surfaces

Reference: Pietikäinen M, Nurmela T, Mäenpää T & Turtinen M (2003) View-based recognition of real-world textures. Pattern Recognition 7(32):313-323.

Due to the changes in viewpoint and illumination, the visual appearance of different surfaces can vary greatly

- textures are modeled with multiple histograms of micro-textons extracted with the LBP operator
- provides the leading performance in the classification of CUReT textures taken from different view angles and illuminations
- very promising results in the classification of outdoor scene images
- an approach to learning appearance models for view-based texture recognition using self-organization of feature distributions is also proposed

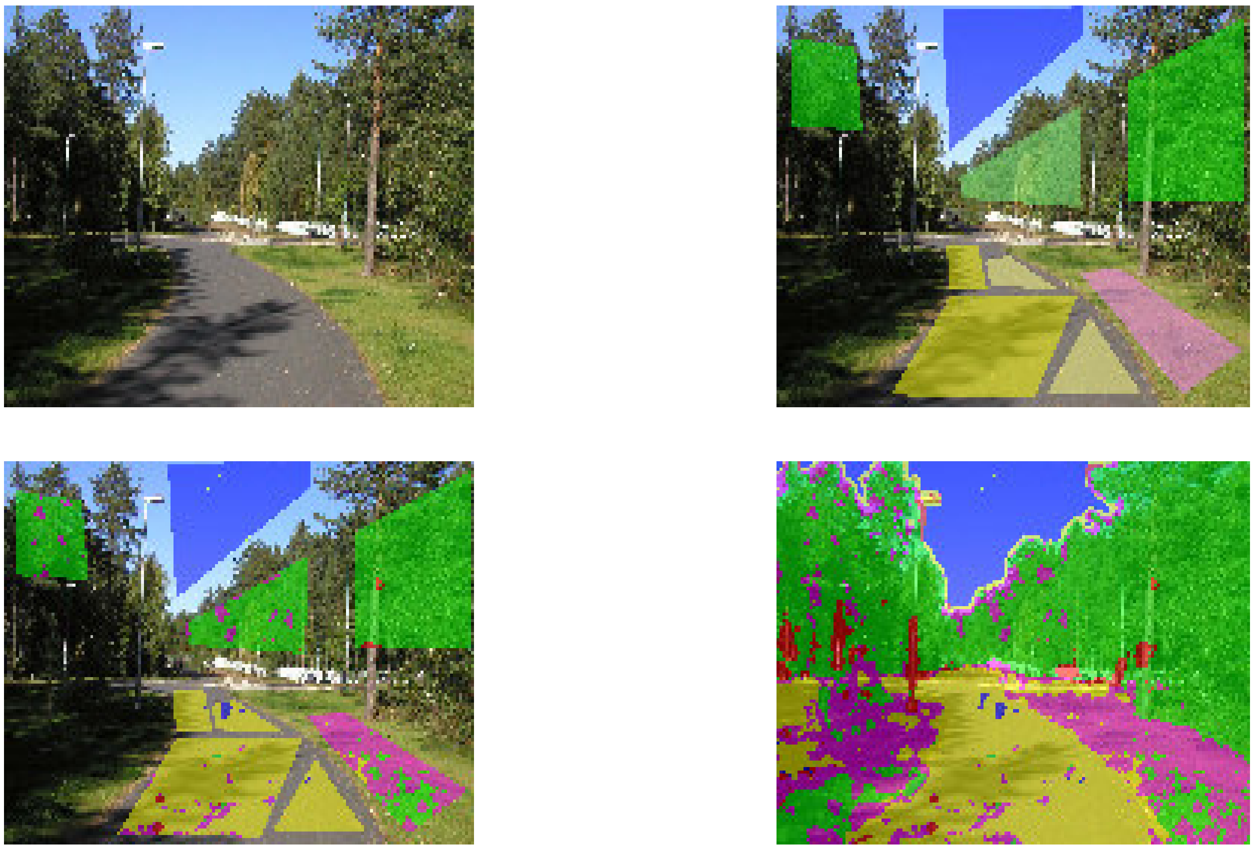
Example of view-based classification

(a) The original image

(b) Ground-truth regions

(c) Classified pixels within ground-truth regions

(d) Segmented image



Visual training for scene classification

Reference: Turtinen M & Pietikäinen M (2003) Visual training and classification of textured scene images. Proc. 3rd International Workshop on Texture Analysis and Synthesis, October 17, Nice, France, 101-106.

Classification of textures in scene images is very difficult due to the high variability of the data within and between images

- a visualization-based approach for training a classifier is presented
- LBP features and the self-organizing map (SOM) are combined
- very promising results are obtained in the classification of outdoor scene images

Application studies

Reference: Kyllönen J & Pietikäinen M (2000) Visual inspection of parquet slabs by combining color and texture. Proc. IAPR Workshop on Machine Vision Applications (MVA'00), November 28-30, Tokyo, Japan, 187-192.

Classification of parquet defects using color percentile and texture features

1. very non-homogeneous textures
2. simple color percentile features performed best
3. a measure combining color percentile and LBP-based texture information further improved the performance
4. gray-scale variant texture features (e.g. co-occurrence) combined with color percentiles did not perform as well

Application studies (cont.)

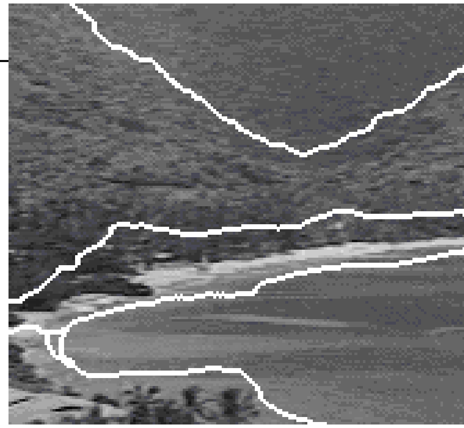
Reference: Turtinen M, Pietikäinen M, Silven O, Mäenpää T & Niskanen M (2003) Paper characterisation using visualisation-based training. The International Journal of Advanced Manufacturing Technology 22(11-12):890-898.

Paper characterization is a very important application area

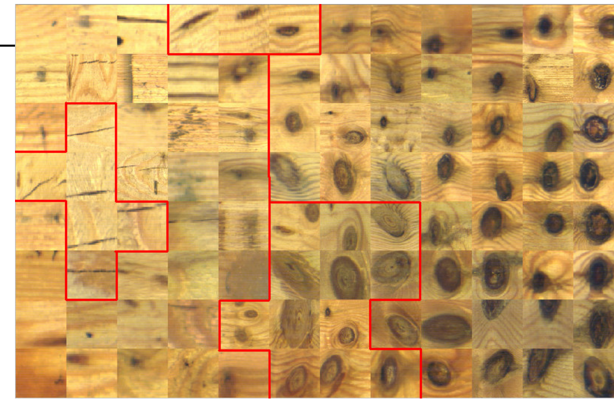
- texture operators with SOM-based training and classification were used

1. LBP provided 40 times better classification accuracy than the methods currently used in paper industry
2. provides capabilities for on-line inspection
3. our approach to paper characterization is being patented

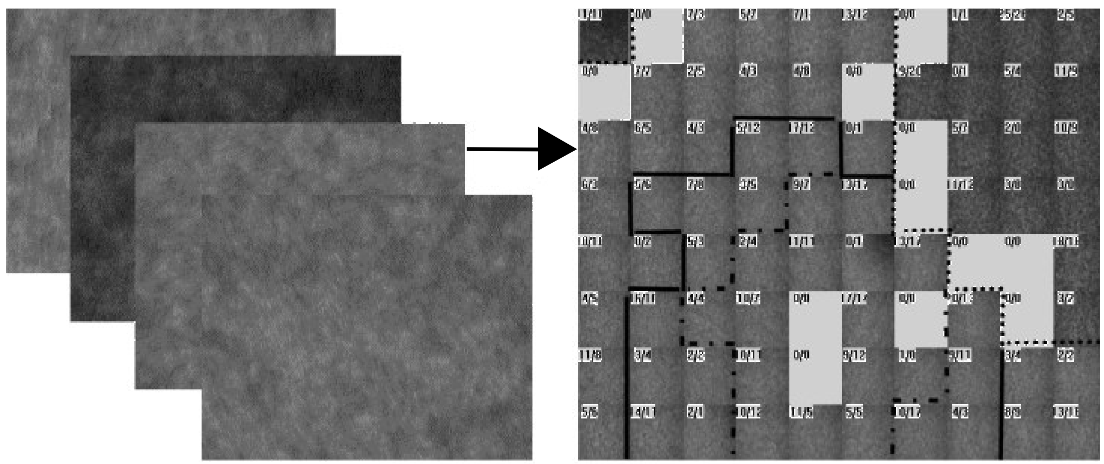
Paper characterization



Texture analysis



Visualization-based training



A breakthrough in paper inspection is expected!

Application studies (cont.)

Reference: Mäenpää T, Turtinen M & Pietikäinen M (2003)
Real-time surface inspection by texture. Real-Time Imaging 9(5):289-296.

A framework for real-time surface inspection with texture

1. combines LBP features with SOM-based classification
2. presents a very fast software implementation of the LBP operator
3. a throughput of 50 images per second is obtained, with an image size of 756x566 pixels

Application studies (cont.)

Reference: Ojala T, Mäenpää T, Viertola J, Kyllönen J & Pietikäinen M (2002) Empirical evaluation of MPEG-7 texture descriptors with a large-scale experiment. Proc. 2nd International Workshop on Texture Analysis and Synthesis, Copenhagen, Denmark, 99-102.

Retrieval of all 319 different textures from the Outex database

1. MPEG-7 texture descriptors: Edge histogram, Homogeneous texture and Texture browsing
2. LBP operators (single and multiresolution)
3. LBP outperformed MPEG-7 descriptors both with respect to retrieval performance and speed of computation

C++ libraries

Reference: Topi Mäenpää (topiolli@ee.oulu.fi)

C++ code for pattern recognition

- includes many of our texture operators

Available at:
http://www.ee.oulu.fi/~topiolli/cpplibs/

General references to LBP

Reference: Mäenpää T (2003) The local binary pattern approach to texture analysis - extensions and applications. Dissertation. Acta Univ Oul C, 78 p + App.

Available in electronic format at:
http://herkules.oulu.fi/isbn9514270762/

Reference: Mäenpää T & Pietikäinen M (2004) Texture analysis with local binary patterns. In: Chen CH & Wang PSP (eds) Handbook of Pattern Recognition & Computer Vision, 3rd ed, World Scientific, Singapore, in press (invited chapter).

New results

Facial image analysis

References:
Ahonen T, Hadid A & Pietikäinen M (2004) Face recognition with local binary patterns. Computer Vision, ECCV 2004 Proceedings, Lecture Notes in Computer Science 3021, Springer, 469-481.
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Detection of moving objects

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Conclusions

- simple theory
- computational simplicity
- invariance wrt. any monotonic transformation of the gray scale
- powerful rotation-invariant analysis with 'uniform' patterns
- excellent discrimination of various kinds of textures
- nonparametric classification principle
- incorporates both structural and statistical texture analysis
- very promising results in application studies
- LBP can be useful in many tasks that have not previously been considered texture analysis problems