LBP-based Texture Descriptors

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Introduction

Texture - *"A textured area in an image can be characterized by a nonuniform or varying spatial distribution of intensity or color"* - Pietikäinen *et.al* 2011

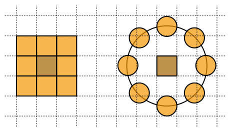
Well known texture features

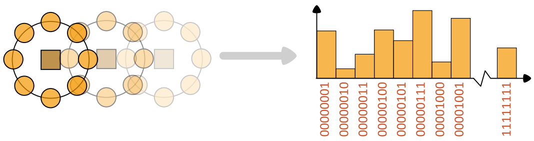
- Haralick features (Haralick 1972)
- Gabor filters (Gabor 1946, (in 2D, Granlund 1978))
- Local Binary Patterns (Ojala 1996)

Local Binary Patterns

- explained in one slide

a) Threshold neighbouring values using center pixel value. **b)** Traverse over the image repeating step *a*. **c)** Compile a histogram over occurring binary sequences.





Local Binary Patterns

- explained in one slide

The local binary code using N samples on a radius R for a pixel position (x, y) is defined as:

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

where

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & otherwise \end{cases} . \quad (2)$$

and g_c is the gray value at (x,y) and g_p the gray value at point p.

Local Binary Patterns

- variants

LBP - Developed in mid '90s as a local contrast descriptor. Initially used in computer vision, now more general use.

The noise sensitivity of LBP soon lead people to develop LBP-based descriptors keeping more of the local information.

- **I**mproved (mean) **L**ocal **B**inary **P**atterns
- **M**edian Local **B**inary **P**atterns
- **L**ocal **T**ernary **P**atterns
- **I**mproved **L**ocal **T**ernary **P**atterns
- **L**ocal **Q**uinary **P**atterns
- **R**obust **LBP**
- **S**hift **LBP**
- **F**uzzy/Soft **LBP**

Improved Local Binary Patterns

$$ILBP_{N,R}(x,y) = \sum_{p=0}^{N-1} s(g_p - g_{mean})2^p + s(g_c - g_{mean})2^N, \quad (3)$$

where

$$g_{mean} = \frac{1}{N+1}\left(\sum_{p=0}^{N-1} g_p + g_c\right), \quad (4)$$

Median Binary Patterns

$$MBP_{N,R}(x,y) = \sum_{p=0}^{N-1} s(g_p - g_{median})2^p + s(g_c - g_{median})2^N, \quad (5)$$

Local Ternary Patterns

$$LTP_{N,R}(x,y) = \sum_{p=0}^{N-1} s_3(g_p,\ g_c,\ t_1)2^p, \quad (6)$$

where

$$s_3(g_p,\ g_c,\ t_1) = \begin{cases} 1, & g_p \geq g_c + t_1 \\ 0, & g_c - t_1 \leq g_p < g_c + t_1 \\ -1, & otherwise \end{cases} . \quad (7)$$

Two binary codes are used to code for 1 and -1 respectively. The two resulting histograms are then concatenated to form the feature vector.

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Improved Local Ternary Patterns

$$ILTP_{N,R}(x,y) = \sum_{p=0}^{N-1} s_3(g_p - g_{mean})2^p + s_3(g_c - g_{mean})2^N, \quad (8)$$

where

$$s_3(g_p,\ g_c,\ t_1) = \begin{cases} 1, & g_p \geq g_c + t_1 \\ 0, & g_c - t_1 \leq g_p < g_c + t_1 \\ -1, & otherwise \end{cases} . \quad (9)$$

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Local Quinary Patterns

$$LQP_{N,R}(x,y) = \sum_{p=0}^{N-1} s_5(g_p,\ g_c,\ t_1,\ t_2)2^p, \quad (10)$$

where the two thresholds are used in the s_5-function according to:

$$s_5(g_p,\ g_c,\ t_1\ t_2) = \begin{cases} 2, & g_p \geq g_c + t_1 \\ 1, & g_c + t_1 \leq g_p < g_c + t_2 \\ 0, & g_c - t_1 \leq g_p < g_c + t_1 \\ -1, & g_c - t_2 \leq g_p < g_c - t_1 \\ -2, & otherwise \end{cases} . \quad (11)$$

Four binary codes are used to code for $2, 1, -1$ and -2 respectively. The four resulting histograms are then concatenated to form the feature vector.

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Robust Local Binary Patterns

$$RLBP_{N,R}(x,y,k) = \sum_{p=0}^{N-1} s(g_p - g_c - k)2^p, \quad (12)$$

where

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & otherwise \end{cases} . \quad (13)$$

k is typically set to a small value like 3 or 4.

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Shift Local Binary Patterns

$$SLBP_{N,R}(x,y,k) = \sum_{p=0}^{N-1} s(g_p - g_c - k)2^p, \quad (14)$$

where k is defined as:

$$k \in [-l,\ l] \cap \mathbb{Z}\,. \quad (15)$$

The number of generated binary patterns K for one pixel position equals the number of different values k assumes;

$$K = 2 \cdot l + 1. \quad (16)$$

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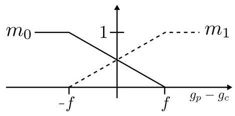
Fuzzy Local Binary Patterns (1/3)

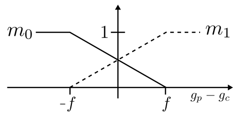
A membership function for a neighbouring point p to a '0-class', m_0, and the antonym function m_1, expressing belongingness to a '1-class' is defined as:

$$m_0(p,f) = \begin{cases} 0, & g_p \geq g_c + f \\ \frac{f - g_p + g_c}{2 \cdot f}, & g_c - f \leq g_p < g_c + f \\ 1, & \textit{otherwise} \end{cases} , \quad (17)$$

$$m_1(p,f) = 1 - m_0(p) \quad . \quad (18)$$



Fuzzy Local Binary Patterns (2/3)



f governs the interval of fuzzy belongingness. The contribution from one pixel position (x, y) to a bin i in the histogram H of occurring binary patterns is:

$$FLBP_{N,R}(x,y,i) = \prod_{p=0}^{N-1} \left[b_p(i) m_1(g_c - g_p) + (1 - b_p(i)) m_0(g_c - g_p) \right] , \quad (19)$$

where $b_p(i) \in \{0, 1\}$ is the value of the p-th bit of the binary representation of pattern i.

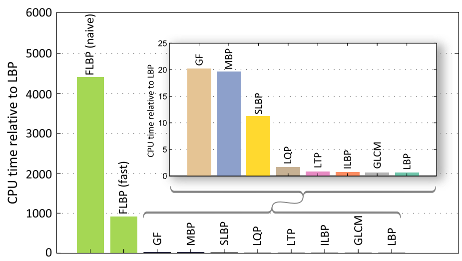
Fuzzy Local Binary Patterns (3/3)

By remembering that all considered pixel positions may contribute to bin i in the histogram H it follows that:

$$H_{FLBP}(i) = \sum_{x,y} FLBP_{N,R}(x,y,i) \; . \quad (20)$$

Analogous to the other LBP-based descriptors, the resulting histogram constitutes the FLBP feature vector.

CPU Time



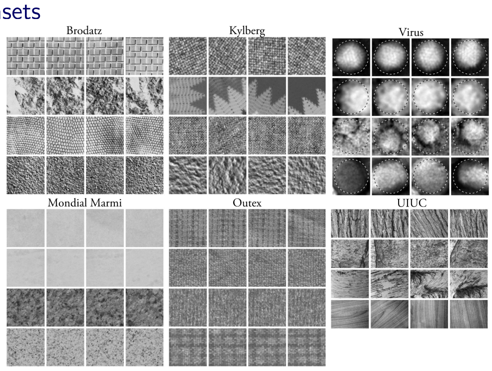
A faster FLBP implementation is achieved by only calculating memberships for positions falling within the fuzzy region $[-f, f]$. Outside the fuzzy region the standard LBP is computed.

Datasets

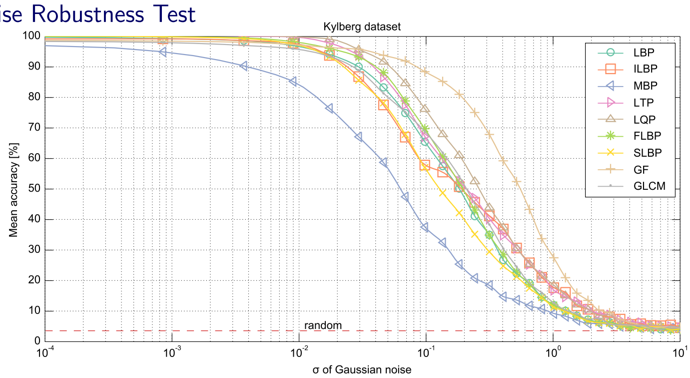
Dataset	No. classes	No. samples per class	Total no. samples	Sample size [px]
Brodatz[a]	111	9	999	213 × 213
Kylberg[b]	28	640	17,920	288 × 288
Mondial Marmi[b]	12	16	192	272 × 272
Outex[c]	24	20	480	128 × 128
UIUC	25	40	1,000	640 × 480
Virus	15	100	1,500	41 × 41

[a] Dataset accessed via (?). [b] Each original sample is divided into four samples.
[c] The Outex texture set Outex_TC_00000 is used.

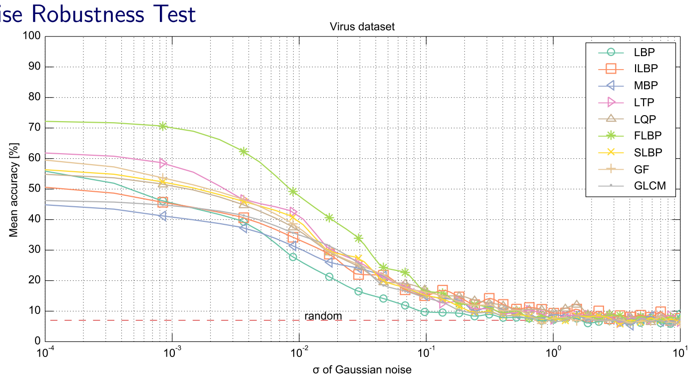
Texture Datasets



Noise Robustness Test



Noise Robustness Test



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Remarks

- Many LBP-based descriptors has been introduced using different encoding and thresholding schemes but there are few comparative studies and few pointers to when to use what.
- The LBP-based descriptors vary in performance and no one seems to be superior to all the others.
- MBP tend to perform poorly (the possible binary patterns are restricted when using the median value).
- FLBP may perform well in specific situations.
- FLBP is very slow compared to the other LBP based descriptors.

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References

- For a good overview of most of the LBP-descriptors see the recent book: "Computer Vision Using Local Binary Patterns" by Pietikäinen, Hadid, Zhao, and Ahonen, Springer London, 2011, 40, 135-148.
- MATLAB implementation of LBP: `http://www.cse.oulu.fi/CMV/Downloads/LBPMatlab`
- For MATLAB implementations of ILBP, MBP, LTP, ILTP, LQP, SLBP, RLBP, FLBP (and also multiscale LBP) just contact me (gustaf@cb.uu.se). My ambition is to document and put the implementations on the CBA wiki (`http://www.cb.uu.se/wiki/`)

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