Enhanced Local Binary Covariance Matrices (ELBCM) for texture analysis and object tracking

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Outline

Introduction: ELBCM characteristics

Enhanced Local Binary Covariance Matrix (ELBCM) proposes:

- A novel way to represent textures using local binary patterns (**LBP's**) and covariance descriptors.
- Averages and covariances of LBP's codes have no textural interpretation.
- ELBCM is based on the angles described by the uniform LBP patterns (**ULBP's**) and not on their codes (decimal values).

Advantages:

- + compact and robust.
- - affected by noise and small rotations.

Introduction: Texture analysis

Why are textures important?

- Textures provide strong cues for object and material recognition.
- Useful to recognize object and material properties such as: hardness, smoothness and opaqueness.

Possible difficulties:

- Intra-class variation.
- Clutter.
- Occlusions.
- Changes in scale, illumination and pose.

Introduction: Methods

Some popular texture analysis methods are:

- Statistical: Co-occurrence matrices and histograms [2].
- Primitive combination: spots, bars, edges, etc.
- Signal-processing based: Filter banks, Wavelets [9],Gabor filtering [7], etc.
- Key-point descriptors: Harris [4], SIFT [6], SURF [1].
- Texture classifiers (using Machine Learning): SVM's[11]), AdaBoost, etc.

Local Binary Patterns (LBP)

- The $\mathrm{LBP}_{P,R}(x_c, y_c)$ operator compares P pixels regularly distributed across the circle of radius R and centre (x_c, y_c).
- A P-length binary code of is formed comparing the value at the center with pixels in the neighbourhood.
- A weight is associated to their position as powers of two $\{2^0, 2^1, \cdots, 2^{P-1}\}$, and accumulating their thresholded differences

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

  , where $s(z)$ is the step function.
- A P-pixel LBP operator maps to 2^P possible labels.

Local Binary Patterns (LBP)

LBP Original Form

example		
6	5	2
7	6	1
9	8	7

thresholded		
1	0	0
1		0
1	1	1

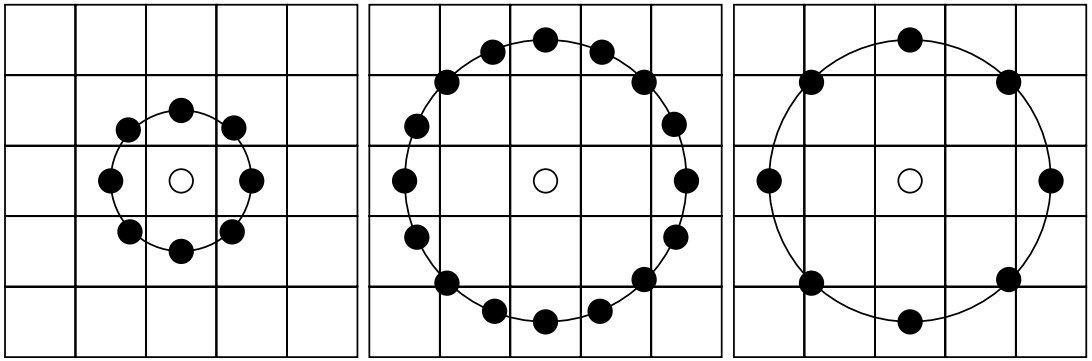
weights		
1	2	4
128		8
64	32	16

Pattern = 11110001

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

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

LBP Ciruclar Forms



$LBP_{8,1}(x_c, y_c)$ (a) $LBP_{16,2}(x_c, y_c)$ (b) $LBP_{8,2}(x_c, y_c)$ (c)

Covariance region descriptors

- Covariance matrix representations [13, 10] and [5] are very practical to build models based on local feature correlations.
- Commonly used features:
  - pixel coordinates,
  - brightness and colour,
  - gradients,
  - optical flow, etc.
- **Considerations**:
  - Covariance descriptors are SPD (symmetric positive-definite) matrices of size $n \times n$, where n is the length of the feature vector.
  - Euclidean geometry is not applicable to compute matrix distances in this set.
  - Distances are measured using geodesics.

Covariance region descriptors: Texture analysis

Gabor based:

- Pang et al. use Gabor filter bank responses to form their Gabor Region Covariance Matrix (GRCM) [8] and [12].
- Highly discriminant.
- Due to the large number of features used (one for each filter), these models are expensive to compute and match.

LBP-based:

- A complementary representation to the traditional LBP histogram analysis.
- Possible to integrate other sources of information such as spatial correlation, luminance and colour, etc.
  - Local Binary Covariance Matrix (LBCM)[3].
  - Gabor-LBP based Region Covariance Descriptor (GLRCD) [14].

Covariance region descriptors: **GLRCD** and **LBCM**

GLRCD:

- LBP decimal values are included directly in the feature vector.
- **Problems**:
  - Arithmetic operations width LBP values have **no textural meaning**
  - Very unstable for the case of small local neighbourhood rotations.

LBCM:

- Each bit in the pattern acts as an independent feature.
- **Advantages**: Arithmetic operations are well defined, stable for small local neighbourhood rotations.
- **Problem**: The number of features grows with the number of bits in the LBP pattern.

ELBCM descriptor

Using the angles defined by the uniform LBP patterns (**ULBP**), a more compact and stable version of the **LBCM** descriptor is obtained.

- Using a $LBP_{8,R}$ operator there are 58 different codes.
- The starting and ending angles θ_0 and θ_1 of the **ULBP** are used as features in the covariance feature vector.
- θ_0 and θ_1 are converted from polar to Cartesian coordinates to avoid using circular arithmetic:

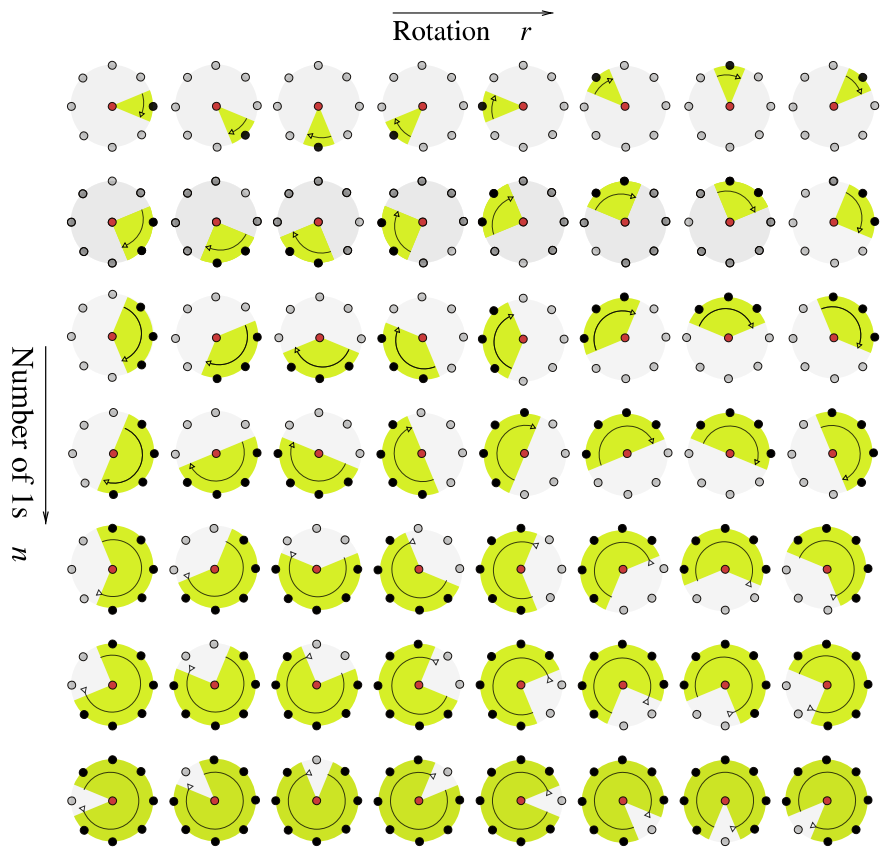
$$\mathbf{v}(\theta_0, \theta_1) = [cos(\theta_0) \;\; sin(\theta_0) \;\; cos(\theta_1) \;\; sin(\theta_1)].$$

- Our Enhanced Local binary Covariance Matrix (**ELBCM**) for texture description is constructed using the mapping function

$$\phi(I, x, y) = \left[\begin{array}{cccc} x & y & I(x,y) & \mathbf{v}(LBP(x,y)) \end{array} \right].$$

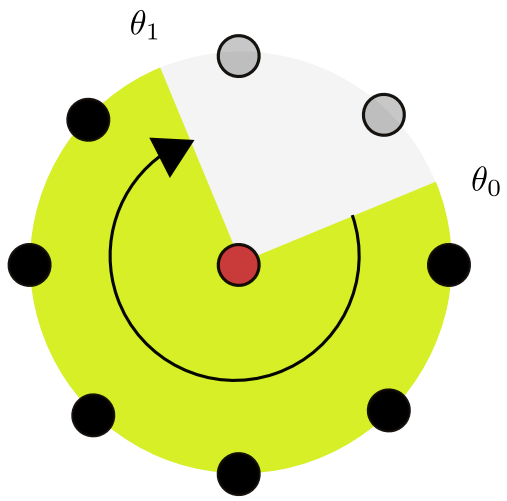
ELBCM descriptor(2)

Example:



(a)

Example: ELBCM mapping for decimal value 63



$$\theta_0 = \frac{\pi}{8} \rightarrow (cos(\theta_0), sin(\theta_0))$$

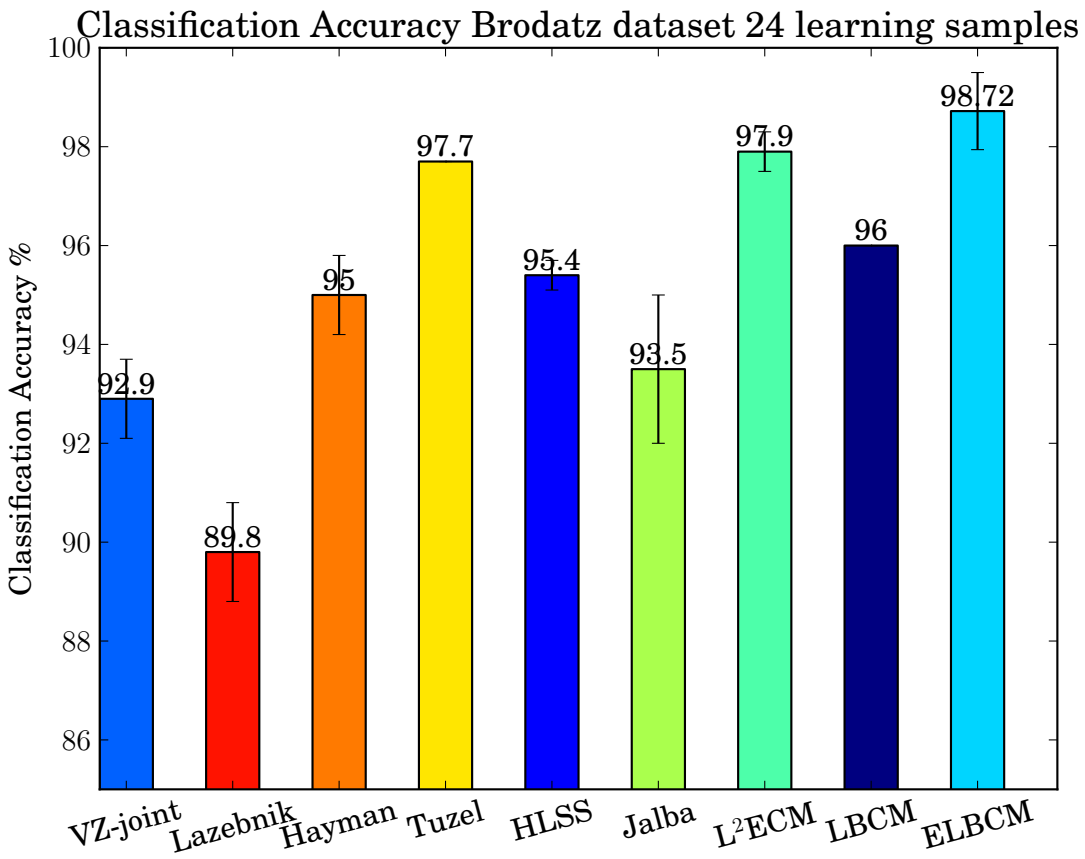
$$\theta_1 = \frac{5\pi}{8} \rightarrow (cos(\theta_1), sin(\theta_1))$$

$$\mathbf{v}(\theta_0, \theta_1) = [cos(\theta_0) \;\; sin(\theta_0) \;\; cos(\theta_1) \;\; sin(\theta_1)]$$

(b)

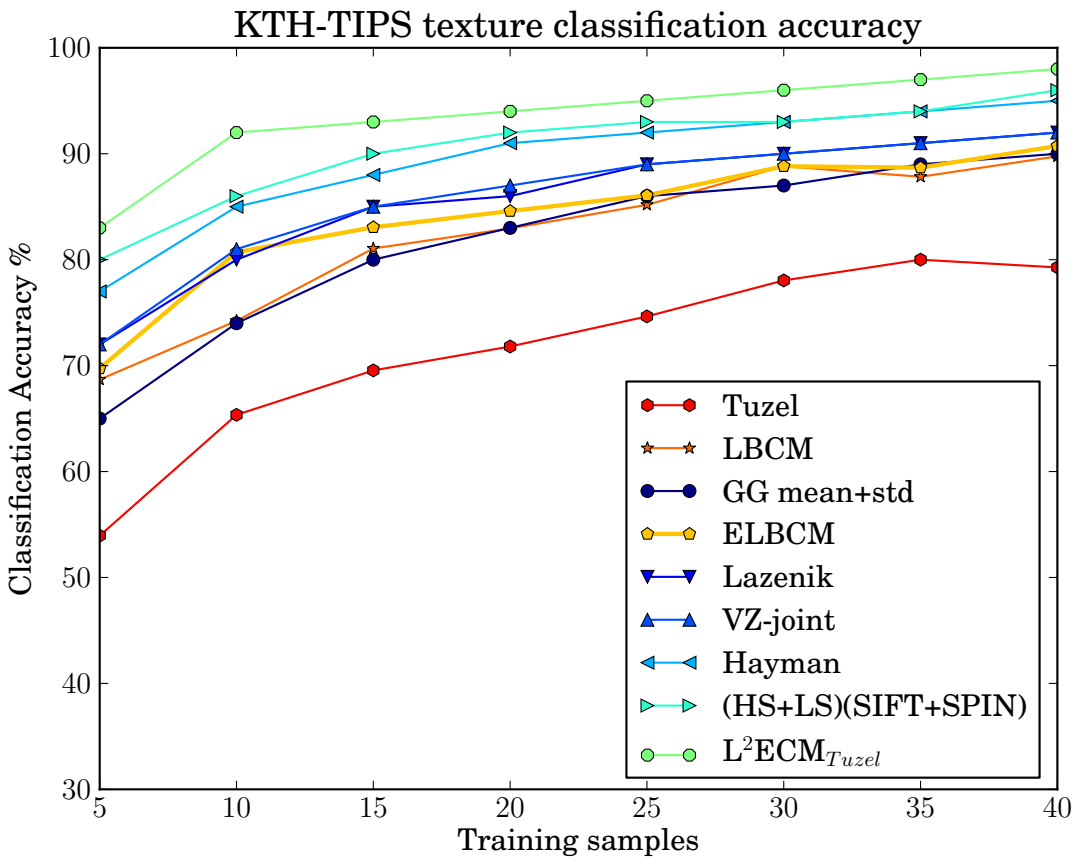
Experiments: Texture analysis

Texture classification Brodatz dataset:



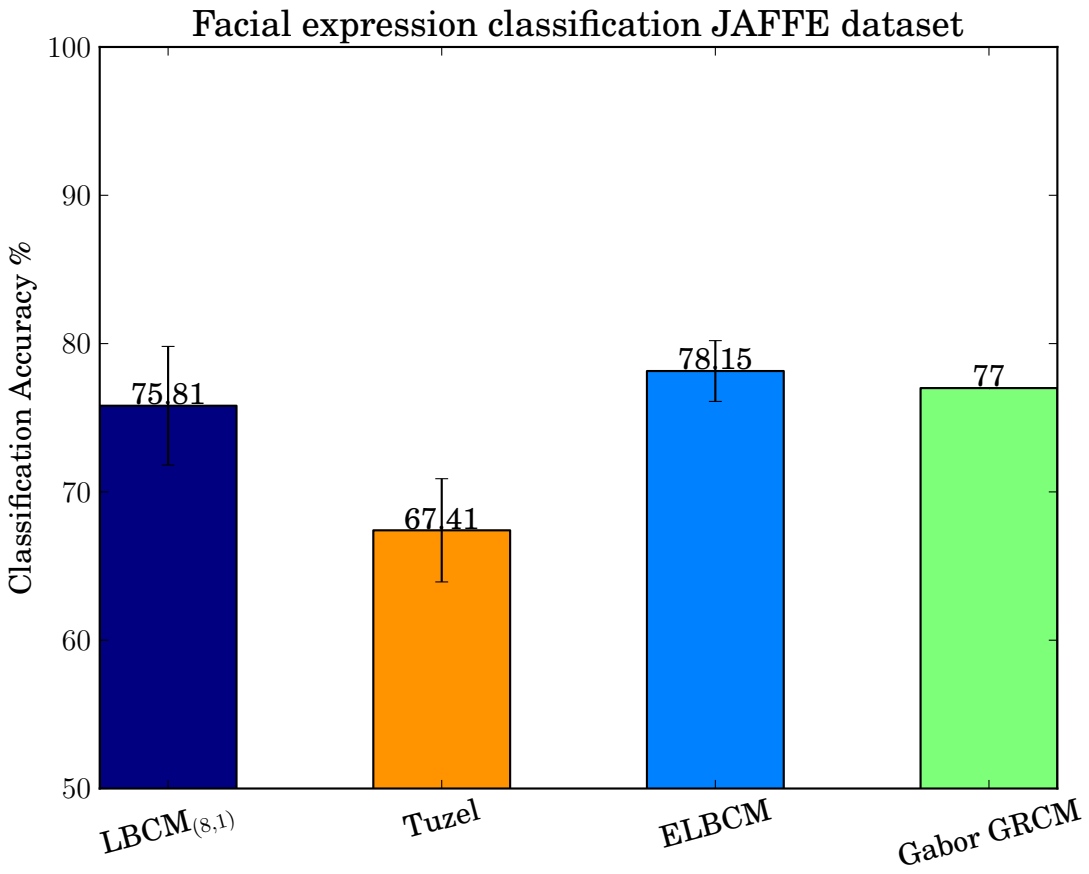
Experiments: Texture analysis(2)

Texture classification KTH-TIPS dataset:

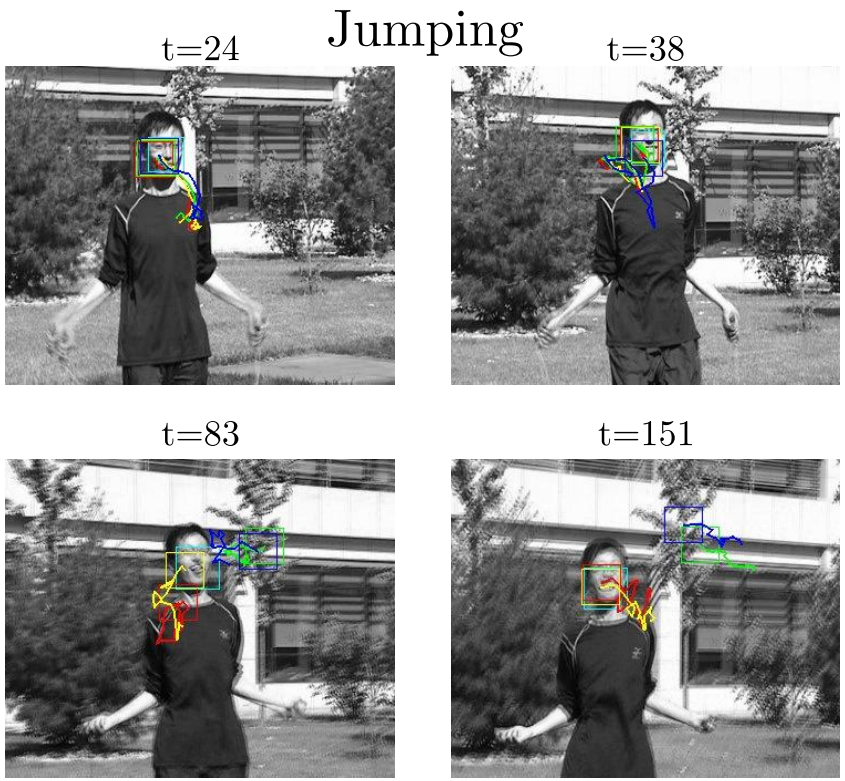


Experiments: Texture analysis(3)

Facial expression classification results for the JAFFE database using 21 learning samples:



Experiments: Object tracking



Tracking results Jumping sequence		
Features	time/frame [ms]	w_{error}
Tuzel	4.83	1.83294
LBCM	10.3	0.362136
ELBCM	4.82	0.268516
LRCD	2.25	2.35453

Experiments: Object tracking (2)

Panda

$t = 221$

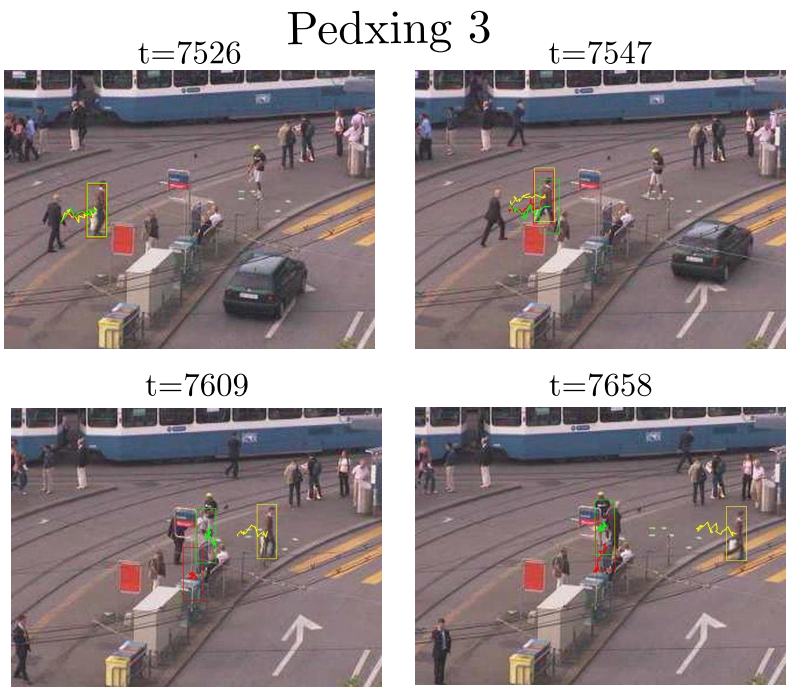
$t = 994$

$t = 1474$

$t = 1657$

Tracking results Panda sequence		
Features	time/frame [ms]	w_{error}
Tuzel	3.65	1.9342
LBCM	7.57	0.282194
ELBCM	3.65	0.279785
LRCD	1.71	0.388786

Experiments: Object tracking (3)



Tracking results Pedxing3 sequence		
Features	time/frame [ms]	w_{error}
Tuzel	20.5	-
LBCM	40.6	-
ELBCM	20.5	-
LRCD	6.69	-

Conclusions

- ELBCM can be used for texture analysis and tracking applications.
- It is more robust, precise and compact than other similar LBP-Covariance matrix approaches.
- Its performance rivals with more elaborated and consuming techniques.

Thanks!

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