Local Angular Patterns for Color Texture Classification

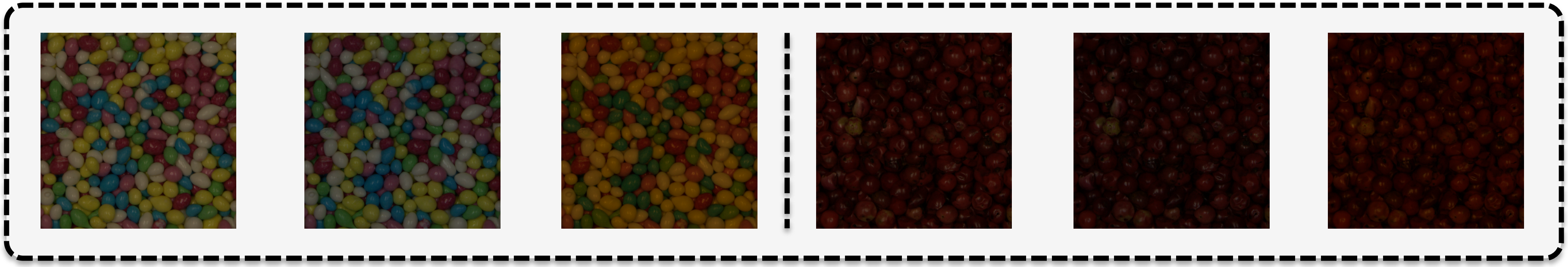
@ Workshop on Color Texture and Material Recognition Recognition 2015

Authors: Claudio Cusano, **Paolo Napoletano**, Raimondo Schettini

Color in Texture classification?

Research question:

it is still not completely clear how much and under what circumstances color information is beneficial.



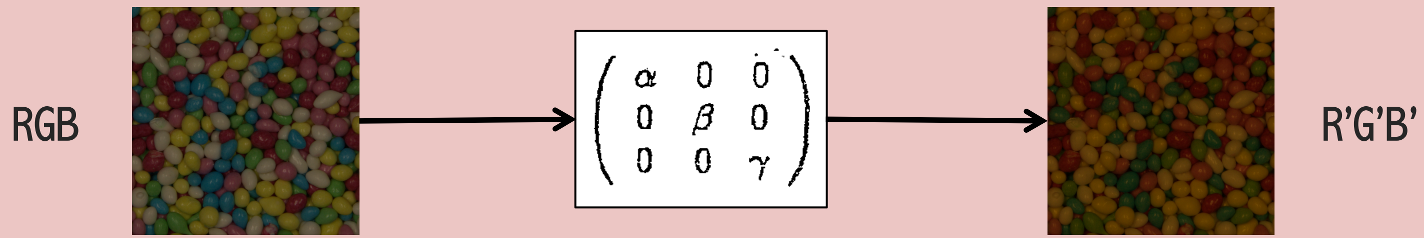
Previous findings:

1. Several works demonstrated that color can be effective only in those cases where illumination conditions do not vary too much between training and test sets;
2. A possible strategy consists in the extraction of image features that are invariant with respect to changes in the illumination;
3. Illumination variations can be also compensated by preprocessing images with a **color normalization.**

Dealing with illumination changes

Assumption: If we assume a simplified illumination model, some descriptors are capable of exploiting color information while, at the same time, staying invariant to illumination changes.

Example: It has been demonstrated how, under a **diagonal illumination** model in the RGB color space, the relative order of pixels values is preserved.



Original **Local Binary Patterns (LBP)** are invariant with respect to scalings of the color channels, that is, they are invariant with respect to the diagonal illumination model.

In practice: illumination changes do not follow the diagonal illumination model because of the presence of acquisition noise and of non-linear interactions between the illuminant, the sample and the camera

In fact, all the proposed solutions that ground on simplified illumination models are not effective

Proposed solution: **P3** a new **color space**

(Part 1)

Most used solution: the luminance value L = 0.299R+ 0.587G + 0.114B is very robust to illumination changes. However its robustness is paid in terms of the amount of information lost during the conversion.

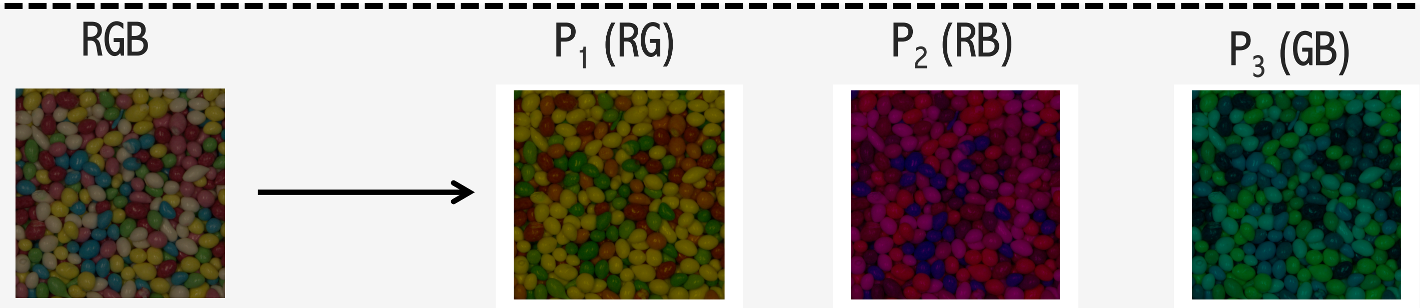
Solution: a new color space that keeps part of the advantages of using the luminance, while preserving the color information.

<u>Color TRANSFORMATION/PROJECTION:</u>

$$\begin{pmatrix} P_1 \\ P_2 \\ P_3 \end{pmatrix} = \begin{bmatrix} 0 & 0.587 & 0.114 \\ 0.299 & 0 & 0.114 \\ 0.299 & 0.587 & 0 \end{bmatrix} \times \begin{pmatrix} R \\ G \\ B \end{pmatrix}$$

TRANSFORMATION PROPERTIES

- **Full-rank:** it preserves all the color information
- **Positive Coefficients:** transformation enjoys the order preserving property of RGB under the diagonal model.



Proposed solution: **Local Angular Patterns (LAP)** (Part 2)

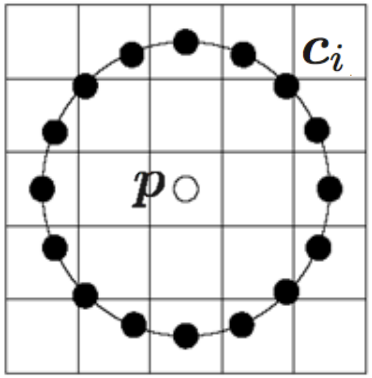
A new descriptor which is invariant with respect to other transformations of the color space (i.e. rotations, reflections, uniform scalings, and their combinations).

Rationale: the angle between two colors is invariant with respect to similarity transformations.

We calculate the angles:

$$\beta_i = \cos^{-1}\left(\frac{\boldsymbol{c}_i \cdot \boldsymbol{\mu}}{\|\boldsymbol{c}_i\|\|\boldsymbol{\mu}\|}\right), \quad \alpha = \cos^{-1}\left(\frac{\boldsymbol{p} \cdot \boldsymbol{\mu}}{\|\boldsymbol{p}\|\|\boldsymbol{\mu}\|}\right)$$

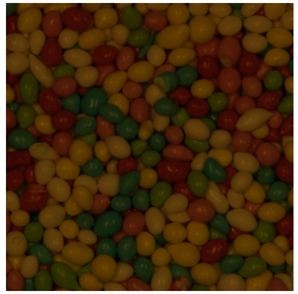
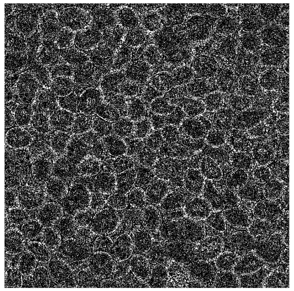
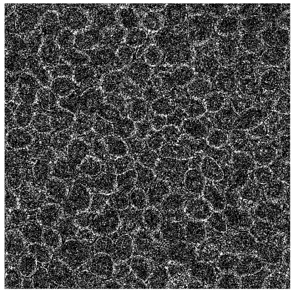
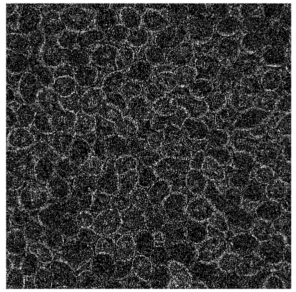
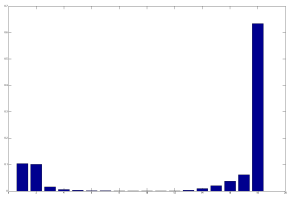
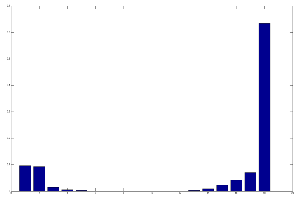
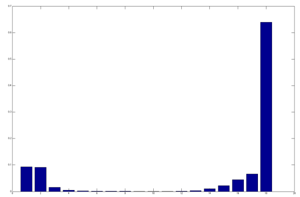
with $\boldsymbol{\mu} = \left(\sum_{i=1}^{n} \boldsymbol{c}_i\right)/n$ the average color of circular neighborhood



LAP: **A pattern of *n* bits** is formed as a result of the comparison between α and $\beta_1, \ldots, \beta_n$ and is treated as standard LBPs: **a histogram of uniform occurrences is formed**.

Proposed solution: **LAP examples**

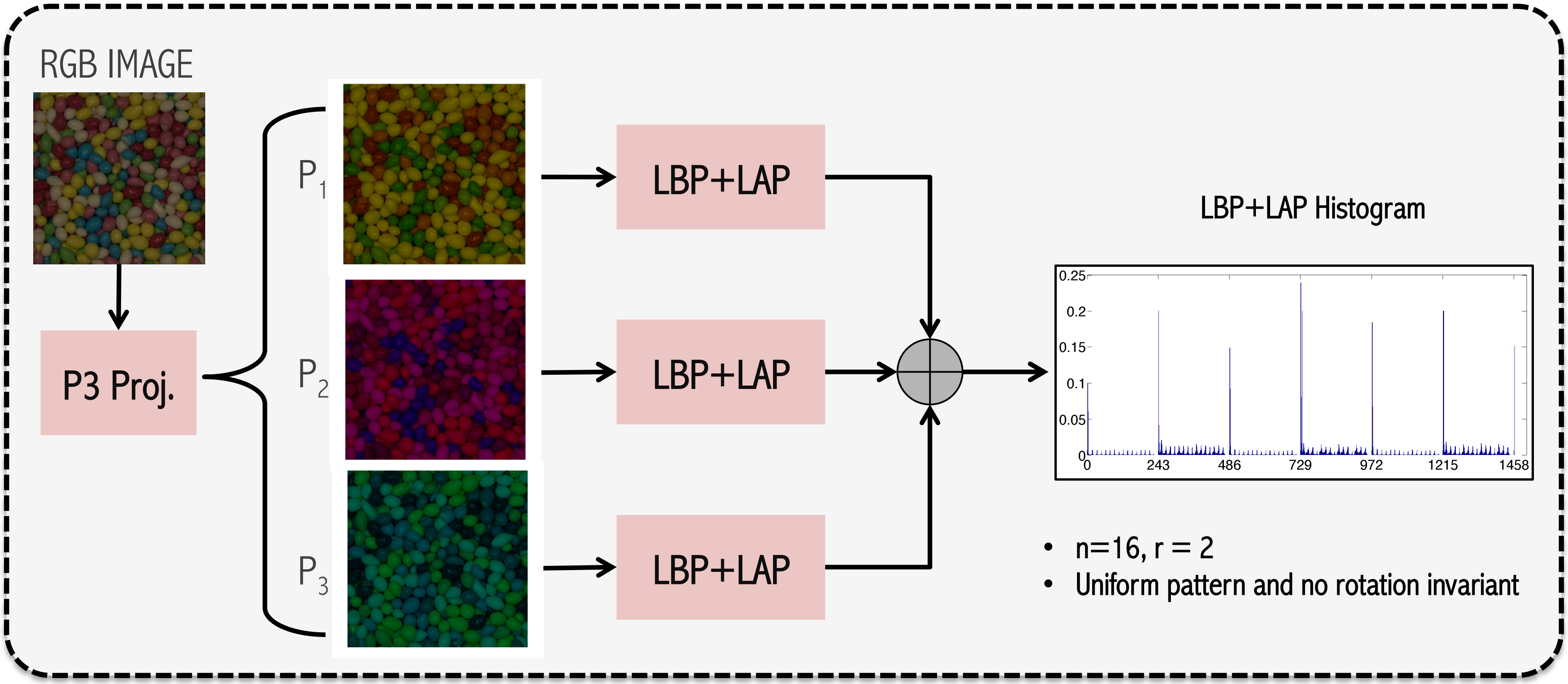
(Part 2)

	D65 (θ=90°)	D95 (θ=90°)	L27 (θ=90°)
ORIGINAL IMAGE (RGB)			
LAP IMAGE			
LAP HISTOGRAM			

Proposed solution: new **visual descriptor**

(Part 3)

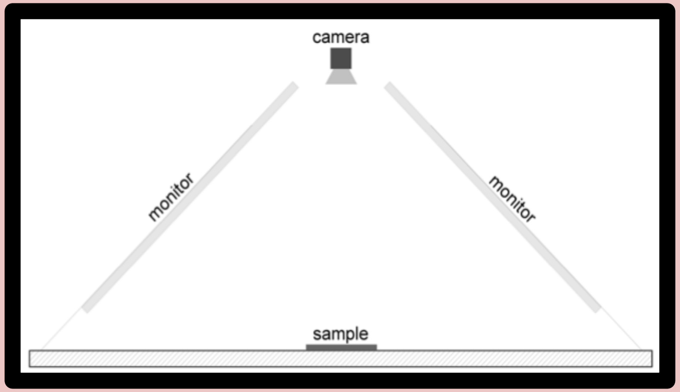
1. We computed a LAP histogram for each channel of the P3 space.
2. The final descriptor is formed by concatenating the three histograms with the three obtained by computing standard LBPs on the three components of the P3 space.



Raw Food Texture (RawFooT*) Database

Specially designed to investigate the robustness of descriptors and classification methods with respect to variations in the lighting conditions:

intensity, direction or in a combination of these factors



- Pictures have been acquired in a **dark room** with a **Canon EOS 40D DSLR** camera;
- **22 in. Samsung SyncMaster LED** monitor;
- **3944×2622** picture converted to sRGB;
- Textures: crop of the central **800×800** pixels.

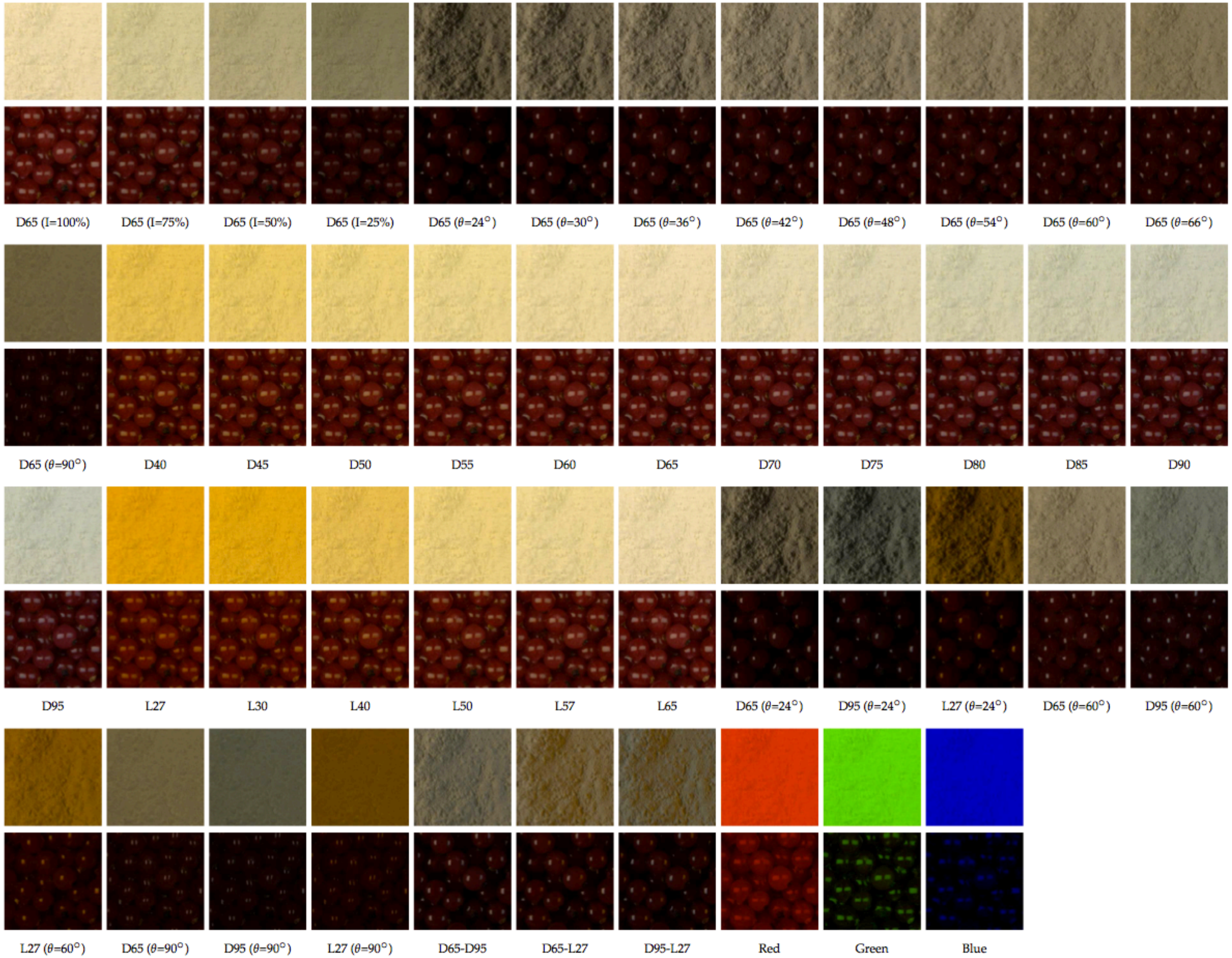
Details:

- **68** samples of raw food (meat, fish, cereals, fruit etc);
- **46** lighting conditions;
- **68** × 46 = 3128 images;
- **46** shots of a 24 squares **Macbeth ColorChecker**.

***Evaluating color texture descriptors under large variations of controlled lighting conditions**

(Claudio Cusano, Paolo Napoletano, Raimondo Schettini) submitted to JOSA A, 2015

RawFooT: 46 lighting conditions



RawFooT: 68 food classes

Experiments

We used the **nearest neighbor classification** strategy with the **L1 distance**.

Performance is reported as **classification rate** (i.e., the ratio between the number of correctly classified images and the number of test images).

Experiment 1
For the comparison we selected a number of descriptors from several classes of approaches: color based, statistical, spectral, structural and hybrid.

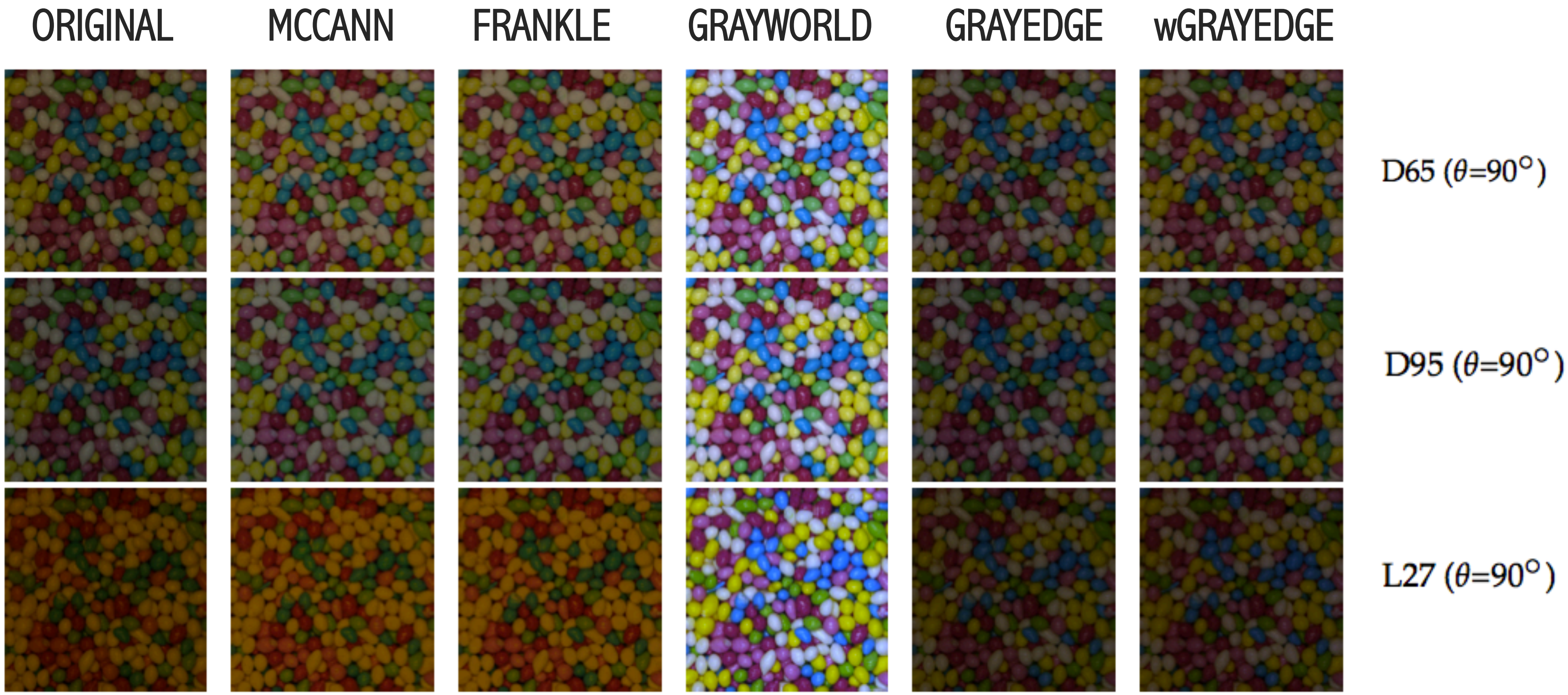
Experiment 2
we experimented several existing normalization methods: McCann, Frankle, Gray World, Gray Edge, Weighted Gray Edge

EXPERIMENTAL SETUP

- For each of the 68 classes we considered 16 non-overlapping squares of size 200×200 pixels.
- For each class eight patches for training and eight for testing by following a chessboard pattern.
- Subsets of $68 \times (8 + 8) = 1088$ patches: training and test patches under different lighting conditions.
- 364 subsets, grouped in six texture classification tasks: **No variations**, **Light intensity**, **Daylight temperature**, **LED temperature**, **Daylight vs. LED**, **Color directions**

Experiments

Illumination variations can be also compensated by preprocessing images with a **color normalization method**.



Experiment 1: **results**

Features	No variations avg (min)	Light intensity avg (min)	Daylight temp. avg (min)	LED temp. avg (min)	Daylight vs LED avg (min)	Temp. & Dir. avg (min)	Rank avg
Hist. L	78.32 (60.66)	6.77 (1.47)	49.94 (11.95)	27.18 (5.88)	38.05 (6.43)	10.45 (1.29)	19.67
Hist. H V	96.38 (84.56)	31.45 (14.52)	49.11 (9.93)	51.56 (23.35)	44.39 (9.19)	16.47 (4.23)	12.33
Hist. RGB	94.93 (87.13)	15.89 (3.12)	56.45 (18.20)	37.51 (12.68)	43.44 (8.00)	15.53 (2.76)	14.83
Hist. *rgb*	**97.24** (92.46)	67.08 (36.95)	37.35 (6.43)	17.38 (3.31)	25.71 (5.15)	20.16 (2.39)	14.17
Chrom. mom.	82.54 (58.46)	68.43 (48.90)	33.41 (4.96)	18.66 (3.68)	24.16 (5.06)	17.03 (2.21)	17.00
Coocc. matr.	35.33 (9.93)	7.20 (2.02)	23.02 (9.74)	19.01 (6.62)	19.88 (5.61)	3.30 (0.18)	22.50
Coocc. matr. L	18.68 (1.47)	3.32 (0.00)	16.99 (6.99)	9.49 (3.31)	12.94 (2.85)	2.49 (0.00)	24.00
DT-CWT	92.26 (81.62)	21.68 (1.65)	66.29 (25.92)	42.31 (14.34)	49.77 (15.44)	19.23 (3.12)	12.83
DT-CWT L	72.85 (58.09)	10.65 (1.29)	60.13 (27.39)	32.70 (4.04)	44.06 (5.06)	14.70 (1.47)	18.00
Gabor RGB	93.02 (61.76)	66.96 (32.35)	64.81 (20.77)	38.13 (12.13)	48.03 (12.59)	27.18 (3.49)	10.00
Gabor L	72.91 (70.04)	46.57 (18.75)	68.94 (59.56)	67.62 (58.82)	66.86 (53.40)	27.58 (2.57)	9.50
Opp. Gabor	96.15 (59.38)	21.51 (3.49)	67.75 (22.98)	41.78 (14.34)	50.80 (15.07)	20.22 (3.86)	11.17
Gist RGB	66.20 (62.50)	55.06 (31.99)	55.49 (28.31)	36.78 (13.24)	43.41 (13.79)	25.13 (2.76)	15.17
Granulometry	91.98 (51.65)	63.73 (27.76)	69.80 (21.51)	33.58 (6.80)	48.79 (6.34)	22.20 (1.65)	11.67
HoG	46.74 (43.20)	37.52 (24.82)	41.14 (29.60)	35.29 (22.24)	36.30 (19.30)	16.99 (3.49)	18.00
LBP L	80.37 (77.02)	51.15 (17.83)	77.76 (72.24)	70.77 (54.60)	73.15 (55.06)	29.54 (5.51)	7.67
LBP RGB	93.55 (90.81)	68.87 (33.46)	72.40 (24.63)	48.39 (15.07)	56.08 (16.82)	23.72 (0.55)	7.00
LBP Lab	92.90 (88.42)	71.88 (32.54)	70.61 (24.08)	51.53 (21.69)	56.00 (19.49)	27.55 (3.31)	6.33
LBP $I_1I_2I_3$	91.40 (82.90)	66.28 (28.12)	70.58 (25.92)	49.90 (18.38)	54.76 (17.00)	27.05 (1.10)	8.67
OCLBP	95.92 (92.28)	**78.75** (51.47)	67.92 (19.67)	49.94 (15.81)	53.93 (15.81)	25.73 (1.65)	6.83
LCC	92.92 (88.60)	62.64 (26.84)	88.78 (73.71)	74.25 (46.88)	78.82 (50.64)	31.13 (5.15)	5.00
Proposed							
LBP P3	88.59 (85.85)	56.22 (16.36)	86.37 (79.60)	76.53 (53.49)	79.84 (54.14)	31.50 (4.60)	5.67
LAP	93.76 (89.71)	65.59 (24.26)	**90.02** (75.74)	**76.86** (49.63)	**80.74** (50.46)	**33.11** (3.12)	**3.00**

Experiment 2: **results**

Features	No variations avg (min)	Light intensity avg (min)	Daylight temp. avg (min)	LED temp. avg (min)	Daylight vs LED avg (min)	Temp. & Dir. avg (min)
Histogram *rgb* (H*rgb*)	97.24 (92.46)	67.08 (36.95)	37.35 (6.43)	17.38 (3.31)	25.71 (5.15)	20.16 (2.39)
H*rgb* + McCann	98.66 (95.77)	65.40 (38.60)	32.79 (7.17)	17.54 (2.76)	23.76 (5.70)	16.22 (2.21)
H*rgb* + Frankle	**98.82** (95.77)	66.42 (39.52)	34.81 (6.99)	17.95 (3.12)	24.45 (5.24)	16.73 (2.76)
H*rgb* + Gray-World	98.81 (96.32)	47.87 (19.30)	51.90 (10.48)	22.42 (1.10)	35.12 (0.46)	13.41 (0.00)
H*rgb* + Gray-Edge	98.36 (96.32)	**78.80** (59.38)	64.46 (17.10)	37.95 (8.46)	46.55 (9.47)	**33.42** (6.25)
H*rgb* + W. Gray-Edge	98.16 (84.01)	75.97 (55.15)	**64.62** (18.38)	**38.65** (9.74)	**46.90** (8.46)	33.08 (6.99)
H*rgb* + Compr.Norm.	91.16 (80.88)	52.63 (21.32)	49.06 (10.11)	19.06 (4.04)	31.95 (4.50)	16.35 (0.74)
LBP-RGB (LBP)	93.55 (90.81)	68.87 (33.46)	72.40 (24.63)	48.39 (15.07)	56.08 (16.82)	23.72 (0.55)
LBP + McCann	94.07 (91.18)	69.61 (38.24)	76.21 (31.80)	**56.59** (26.47)	**61.71** (23.71)	**28.42** (2.94)
LBP + Frankle	**94.21** (90.62)	68.37 (33.64)	71.99 (24.45)	47.73 (16.54)	55.40 (16.54)	24.71 (2.21)
LBP + Gray-World	93.63 (90.81)	**80.91** (62.68)	**77.88** (37.68)	47.09 (12.68)	58.19 (13.51)	27.10 (0.74)
LBP + Gray-Edge	94.03 (91.18)	62.96 (27.02)	72.79 (30.33)	44.01 (10.66)	54.02 (13.60)	22.75 (0.37)
LBP + W. Gray-Edge	93.93 (81.62)	63.45 (26.65)	72.83 (27.76)	44.09 (10.85)	53.98 (14.25)	22.95 (0.55)
LBP + Compr. Norm.	93.85 (87.32)	57.63 (17.28)	55.29 (3.12)	20.70 (1.47)	35.02 (1.47)	18.16 (0.00)
LAP	93.76 (89.71)	65.59 (24.26)	**90.02** (75.74)	**76.86** (49.63)	**80.74** (50.46)	33.11 (3.12)
LAP + McCann	91.47 (87.87)	66.82 (30.33)	88.11 (76.65)	72.18 (42.10)	77.34 (44.12)	**34.61** (7.54)
LAP + Frankle	91.86 (86.95)	65.75 (31.07)	88.03 (73.16)	69.18 (38.24)	75.09 (38.97)	32.84 (7.90)
LAP + Gray-World	90.38 (85.66)	**76.18** (54.96)	79.69 (49.82)	49.20 (10.11)	59.58 (10.48)	27.50 (4.78)
LAP + Gray-Edge	92.48 (88.60)	56.57 (18.93)	85.01 (62.13)	58.75 (19.12)	67.87 (22.52)	26.78 (4.04)
LAP + W. Gray-Edge	92.39 (82.35)	56.77 (20.59)	85.07 (61.95)	59.28 (22.43)	68.11 (23.44)	26.84 (4.04)
LAP + Compr. Norm.	**95.86** (90.07)	57.80 (17.28)	61.15 (6.62)	24.83 (0.18)	39.63 (1.93)	20.86 (1.10)

Conclusions

1. Proposed descriptor demonstrated to be effective to a number of lighting condition variations;
2. LAP is not robust to changes in the temperature and direction of the light
3. Color normalization helps in some cases, but is difficult to understand which method is better
4. We evaluated only hand-crafted features, CNN based features must be tested

Questions?

Proposed solution: **Local Angular Patterns** (Part 2)

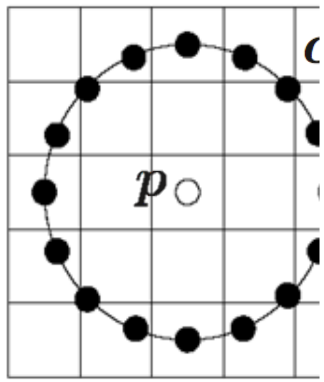
A new descriptor which is invariant with respect to other transformations of the color space (i.e. rotations, reflections, uniform scalings, and their combinations).

Rationale: the angle between two colors is invariant with respect to similarity transformations.

For each pixel $\boldsymbol{p}$, the average color of circular neighborhood $\boldsymbol{c}_1, \ldots, \boldsymbol{c}_n$

$$\alpha = \cos^{-1}\left(\frac{\boldsymbol{p} \cdot \boldsymbol{\mu}}{\|\boldsymbol{p}\|\|\boldsymbol{\mu}\|}\right) \quad \beta_i = \cos^{-1}\left(\frac{\boldsymbol{c}_i \cdot \boldsymbol{\mu}}{\|\boldsymbol{c}_i\|\|\boldsymbol{\mu}\|}\right), \quad i \in \{1, \ldots n\}$$

with $\boldsymbol{\mu} = \left(\sum_{i=1}^{n} \boldsymbol{c}_i\right)/n$



A pattern of *n* bits is formed as a results of the comparison between α and $\beta_1, \ldots, \beta_n$

and is treated as standard LBPs: **a histogram of uniform occurrences is formed**.

In practice, each bit tells whether or not the corresponding neighbor is