Local Angular Patterns for Color Texture Classification

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Abstract. The description of color texture under varying lighting conditions is still an open issue. We defined a new color texture descriptor, that we called Local Angular Patterns, specially designed to be robust to changes in the color of the illuminant. The results show that our descriptor outperforms the state-of-the-art on a dataset of food textures.

1 Introduction

The role of color in texture classification has been widely debated in the literature. Despite the number and the depth of the experimental verifications, it is still not completely clear how much and under what circumstances color information is beneficial. Notable examples of this kind of analysis are the work by Mäenpää and Pietikäinen [14], and that by Bianconi *et al.* [4]. They observed how color can be effective, but only in those cases where illumination conditions do not vary too much between training and test sets. In fact, methods that exploit color information greatly suffer variations in the lighting conditions. A possible strategy to exploit color in texture classification consists in the extraction of image features that are invariant with respect to changes in the illumination. Khan *et al.* [13], for instance, considered a diagonal/offset model for illumination variations, deduced from it an image normalization transformation, and finally extracted Gabor features from the normalized images. Other color normalization techniques can be used for this purpose. Finlayson *et al.* proposed rank-based features obtained from invariant color representations [10]. Seifi *et al.*, instead, proposed to characterize color textures by analyzing the rank correlation between pixels located in the same neighborhood. They obtained a correlation measure which is related to the colors of the pixels, and is not sensitive to illumination changes [16]. The reader can also refer to [3,5–7,9,12]. In this paper we propose a new texture descriptor that has been specially designed to deal with variations of the color of the illuminant. We will show how the proposed descriptor, that we call Local Angular Patterns, outperforms all the other approaches considered.

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2 Proposed Descriptor

Many descriptors have been proposed to encode color and texture information at the same time. Several of them consist just in the replication to multiple color channels of known techniques that have been originally designed for intensity images. The introduction of color information into a texture descriptor improves its capability in discriminating certain types of classes. However, it also increases its sensitivity to changes in the lighting conditions in general and in the illuminant color in particular. 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. For instance, Finlayson *et al.* demonstrated how, under a diagonal illumination model in the RGB color space, the relative order of pixels values is preserved [10] (e.g. redder pixels stay redder independently on the color of the illuminant). Therefore descriptors based on the relative order among pixels (Local Binary Patterns, for instance) should be invariant with respect to the illumination color. However, in practice this is far for the truth, as we will show in the section on the experimental results. In fact, 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 [1,2,4].

The luminance value L, computed from the RGB components as $L = 0.299R + 0.587G + 0.114B$, has been demonstrated to be very robust to illumination changes. Part of its robustness, that is due to the weighted averaging of the color channels, is paid in terms of the amount of information lost during the conversion process. We propose the use of a new color space that keeps part of the advantages of using the luminance, while preserving the color information. The conversion from RGB to this new color space consists in two steps: first the RGB coordinates are projected to the RG, RB and GB planes, then luminance is computed for the three projections. We call this, the P3 color space since it is obtained through three different projections. The transformation from RGB is linear, and corresponds to the following equation:

$$\begin{pmatrix} P_1 \\ P_2 \\ P_3 \end{pmatrix} = \begin{bmatrix} 0 & 0.587 & 0.114 \\ 0.299 & 0 & 0.114 \\ 0.299 & 0.587 & 0 \end{bmatrix} \times \begin{pmatrix} R \\ G \\ B \end{pmatrix}, \tag{1}$$

where P_1, P_2 and P_3 are the components of the new space.

Equation (1) defines a full-rank transformation, therefore it preserves all the color information. Moreover, since none of the coefficients is negative the transformed values enjoy the order-preserving property of RGB under the diagonal illumination model. We will show how the simple substitution of RGB with P3 brings significant improvements in the classification of color textures under varying illumination conditions.

2.1 Local Angular Patterns

Original LBPs are invariant with respect to scalings of the color channels, that is, they are invariant with respect to the diagonal illumination model. We propose a descriptor which is invariant with respect to other kind of transformations of the color space. Interpreting colors as three-dimensional vectors, we may notice how the angle between two of them is invariant with respect to similarity transformations (i.e. rotations, reflections, uniform scalings, and their combinations). Angular information is encoded by the proposed descriptor in a way which is very similar to that used by standard LBPs for the encoding of the pixels' values. Therefore, we call it LAP, since it represents information about Local Angular Patterns.

LAP is computed as follows: for each pixel $\boldsymbol{p}$ a circular neighborhood $\boldsymbol{c}_1, \dots, \boldsymbol{c}_n$ is considered and the average color $\boldsymbol{\mu} = \left(\sum_{i=1}^{n} \boldsymbol{c}_i\right)/n$ is computed. The angle α between $\boldsymbol{p}$ and $\boldsymbol{\mu}$ is computed:

$$\alpha = \cos^{-1}\left(\frac{\boldsymbol{p} \cdot \boldsymbol{\mu}}{\|\boldsymbol{p}\|\|\boldsymbol{\mu}\|}\right), \tag{2}$$

and similar angles $\beta_1, \dots, \beta_n$ are computed for each of the neighbors of $\boldsymbol{p}$:

$$\beta_i = \cos^{-1}\left(\frac{\boldsymbol{c}_i \cdot \boldsymbol{\mu}}{\|\boldsymbol{c}_i\|\|\boldsymbol{\mu}\|}\right), \quad i \in \{1, \dots n\}. \tag{3}$$

A pattern of n bits is formed as a results of the comparison between α and $\beta_1, \dots, \beta_n$. In practice, each bit tells whether or not the corresponding neighbor is more far away from the average than the central pixel. After their computation, the angular patterns are treated as standard LBPs: a histogram of occurrences is formed, possibly by counting in the same bin all the non-uniform (i.e. irregular) patterns.

To combine the advantages of the P3 color space with those of LAP, we adopted the following strategy: we projected the pixels on the RG, RB and GB planes, and we computed three LAP histograms (one for each projection). 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. In this way the descriptor contains parts that are invariant to scalings of the color channels, and parts that are invariant to similarity transformations in the color space. Their combination is thus expected to be robust to a variety of transformations of the color space.

3 Experiments

For the experiments we used the Raw Food Texture database (RawFooT), that has been specially designed to investigate the robustness of descriptors and classification methods with respect to variations in the lighting conditions [8]. Classes correspond to 68 samples of raw food, including various kind of meat, fish, cereals, fruit etc. Samples taken under D65 at light direction $\theta = 24°$ are showed in Fig. 1. The database includes images of 68 samples of textures, acquired under 46 lighting conditions which may differ in:

1. the light direction: 24, 30, 36, 42, 48,54, 60, 66, and 90 degrees;

Fig. 1. Overview of the 68 classes included in the Raw Food Texture database. For each class it is shown the image taken under D65 at direction θ=24°.

2. illuminant color: 9 outdoor illuminants: D40, D45, ..., D95; 6 indoor illuminants: 2700 K, 3000 K, 4000 K, 5000 K, 5700 K and 6500 K, we will refer to these as L27, L30, ..., L65;
3. intensity: 100%, 75%, 50% and 25% of the maximum achievable level;
4. combination of these factors.

For each of the 68 classes we considered 16 patches obtained by dividing the original texture image, that is of size 800×800 pixels, in 16 non-overlapping squares of size 200×200 pixels. For each class we selected eight patches for training and eight for testing by following a chessboard pattern. We form subsets of $68 \times (8 + 8) = 1088$ patches by taking the training and test patches from images taken under different lighting conditions. In this way we defined 364 subsets, grouped in six texture classification tasks.

1. *No variations*: 46 image subsets. Each subset is composed of training and test images taken under the same lighting condition.
2. *Light intensity*: 12 image subsets obtained by combining the 4 intensity variations. Each subset is composed of training and test images with different light intensity values.
3. *Daylight temperature*: 132 image subsets obtained by combining all the 12 daylight temperature variations. Each subset is composed of training and test images with different light temperatures.
4. *LED temperature*: 30 image subsets obtained by combining all the 6 LED temperature variations. Each subset is composed of training and test images with different light temperatures.
5. *Daylight vs. LED*: 72 image subsets obtained by combining 12 daylight temperatures with 6 LED temperatures.
6. *Color directions*: 72 image subsets obtained by combining all the 9 combinations of color temperatures and light directions. Each subset is composed of training and test images with different lighting conditions.

In all the experiments we used the nearest neighbor classification strategy: given a patch in the test set, its distance with respect to all the training patches is computed. The prediction of the classifier is the class of closest element in the training set. For this purpose , after some preliminary tests with several descriptors in which we evaluated the most common distance measures, we decided to use the $L1$ distance: $d(\mathbf{x}, \mathbf{y}) = \sum_{\mathbf{i=1}}^{\mathbf{N}} |\mathbf{x_i} - \mathbf{y_i}|$, where $\mathbf{x}$ and $\mathbf{y}$ are two feature vectors. All the experiments have been conducted under the *maximum ignorance* assumption, that is, no information about the lighting conditions of the test patches is available for the classification method and for the descriptors. Performance is reported as classification rate (i.e., the ratio between the number of correctly classified images and the number of test images).

For the comparison we selected a number of descriptors from several classes of approaches [4,15]: color based, statistical, spectral, structural and hybrid. Most of the considered descriptors have been applied to both color and gray-scale images. The gray-scale image is the luminance of the image and is obtained by using the standard formula: $L = 0.299R + 0.587G + 0.114B$.

The descriptors evaluated are:

- a single 256-dimensional gray level histogram as well as 512- and 768-dimensional color histograms (computed on different color spaces);
- A set of 10 normalized *chromaticity moments* as defined in [4];
- contrast, correlation, energy, entropy and homogeneity features extracted from *co-occurrence matrices*, so obtaining 5 components for each color channel;
- *Gabor* features computed as the mean and standard deviation of four orientations extracted at four frequencies, 96 components for each color channel;
- *opponent Gabor* features extracted from several inter/intra channel combinations;
- *Dual Tree Complex Wavelet Transform* (DT-CWT) features with four scales, two features (mean and standard deviation), and three color channels, so obtaining 24 components;
- morphological features (*granulometries*) to each color channel separately. The number of components used is 78;
- *Gist* features with eight orientations and four scales for each channel, for a total of 1536 components;
- *Histogram of Oriented Gradients* (HOG), in the version described in [11].We considered nine histograms with nine bins that is concatenated to make a 81-dimensional feature vector [11];
- gray *Local Binary Patterns* (LBP) and its color variants applied to different color spaces such as, the RGB, CIE-Lab and Ohta's $I_1I_2I_3$ [14]. We considered 243 LPBs for each color channel;
- combination of LBP computed on pairs of color channels, namely the *Opponent Color LBP* (OCLBP). We considered 243 LPBs for each color channel;
- Local Color Contrast, as defined in [7], with 499 components.

Table 1 reports the performance obtained by the considered and proposed descriptors in each single classification task as *average* and *minimum accuracy*. The last column of the table represents the *average rank* over the six tasks for each descriptor. It is clear that color information is very useful when training and test images are taken under the *same illumination*. In fact, the histogram

Table 1. Evaluation of several texture descriptors. For each classification task, the best result is reported in bold.

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**

Table 2. Accuracy of selected color descriptors combined with different preprocessing methods.

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)

rgb descriptor achieves the best accuracy rate of 97.24% with a minimum value of 92.46%. In this case, also other histogram schemes achieve good performance. The best LBP scheme is the OCLBP with a classification rate of 95.92%. The proposed LAP achieves 93.76% thus occupying the 6th position in this task with a distance of 3.5% from the best. When the light intensity changes, the most robust descriptor is the OCLBP with a classification accuracy of 78.75% and a minimum value of 51.47%. Several color descriptors achieve a classification rate of about 65% (that is about 10% less than the best) with the LAP occupying the 8th position. In contrast, descriptors computed on gray-scale images struggle to deal with such a variability. In the remaining classification tasks, that are the focus of this work, it is clear that both LAP and LBP P3 achieve the best performance. The closest descriptors are: LCC, LBP L, LBP RGB, GABOR L and LBP Lab. In the case of *Daylight temperature* variations, the LBP L achieves a classification rate of about 13% less than the LAP. In both cases of *LED temperature* variations and *Daylight vs LED*, the LBP L achieves a classification rate of about 7% less than the LAP. It is important to point out that all the evaluated descriptors achieve poor performance in the *Temperature and Direction* task (about 30% on average and with a lowest performance below to the 1%). Overall, looking at the average rank column, the proposed LAP is better than existing descriptors.

Illumination variations can be also compensated by preprocessing images with a color normalization method. Color normalization methods try to assign a constant color to objects even under different illumination conditions [7]. In order to evaluate this strategy, we have preprocessed the database by using several existing normalization methods and next we have extracted features by using the best color descriptors from the set of descriptors evaluated in table 1. More precisely, we considered two implementations of the Retinex method: the *McCann99* and the *Frankle-McCann*. Furthermore, we considered the Gray World, two variants of edge based algorithm, the Gray-Edge and the weighted Gray-Edge method, and the Comprehensive Normalization. Table 2 reports the performance obtained by these color normalization methods combined with the selected descriptors. It is clear that color normalization helps to improve performance in the case of *no variations* and *light intensity* variations. In the remaining tasks, histogram *rgb* and LBP RGB achieve better performance, while LAP is negatively influenced by the use of preprocessing.

4 Conclusions

We focused, here, on texture classification under variable light color. To this purpose, we proposed a new descriptor that exploits a novel color space transformation and a novel descriptor based on Local Angular Patterns. Such a descriptor, that has been designed to be robust with respect to scalings of the color channels and to similarity transformations in the color space, significantly outperformed the state of the art.

References

1. Bianco, S., Bruna, A., Naccari, F., Schettini, R.: Color space transformations for digital photography exploiting information about the illuminant estimation process. JOSA A **29**(3), 374–384 (2012)
2. Bianco, S., Bruna, A.R., Naccari, F., Schettini, R.: Color correction pipeline optimization for digital cameras. Journal of Electronic Imaging **22**(2), 023014–023014 (2013)

3. Bianco, S., Cusano, C., Napoletano, P., Schettini, R.: On the robustness of color texture descriptors across illuminants. In: Petrosino, A. (ed.) ICIAP 2013, Part II. LNCS, vol. 8157, pp. 652–662. Springer, Heidelberg (2013)
4. Bianconi, F., Harvey, R., Southam, P., Fernández, A.: Theoretical and experimental comparison of different approaches for color texture classification. J. of Electronic Imaging **20**(4), 043006–043006 (2011)
5. Cusano, C., Napoletano, P., Schettini, R.: Illuminant invariant descriptors for color texture classification. In: Tominaga, S., Schettini, R., Trémeau, A. (eds.) CCIW 2013. LNCS, vol. 7786, pp. 239–249. Springer, Heidelberg (2013)
6. Cusano, C., Napoletano, P., Schettini, R.: Intensity and color descriptors for texture classification. IS&T/SPIE Electronic Imaging, 866113–866113 (2013)
7. Cusano, C., Napoletano, P., Schettini, R.: Combining local binary patterns and local color contrast for texture classification under varying illumination. JOSA A **31**(7), 1453–1461 (2014)
8. Cusano, C., Napoletano, P., Schettini, R.: Evaluating color texture descriptors under large variations of controlled lighting conditions. IEEE Transaction in Image Processing (2015, submitted)
9. Drbohlav, O., Leonardis, A.: Towards correct and informative evaluation methodology for texture classification under varying viewpoint and illumination. Computer Vision and Image Understanding **114**(4), 439–449 (2010)
10. Finlayson, G., Hordley, S., Schaefer, G., Yun Tian, G.: Illuminant and device invariant colour using histogram equalisation. Pattern recognition **38**(2), 179–190 (2005)
11. Junior, O.L., Delgado, D., Gonçalves, V., Nunes, U.: Trainable classifier-fusion schemes: an application to pedestrian detection. In: Intelligent Transportation Systems (2009)
12. Kandaswamy, U., Schuckers, S.A., Adjeroh, D.: Comparison of texture analysis schemes under nonideal conditions. IEEE Transactions on Image Processing **20**(8), 2260–2275 (2011)
13. Khan, R., Muselet, D., Trémeau, A.: Classical texture features and illumination color variations. In: Proc. third Int'l Conf. on Machine Vision, pp. 280–285 (2010)
14. Mäenpää, T., Pietikäinen, M.: Classification with color and texture: jointly or separately? Pattern Recognition **37**(8), 1629–1640 (2004)
15. Mirmehdi, M., Xie, X., Suri, J.: Handbook of Texture Analysis. Imperial College Press, London (2008)
16. Seifi, M., Song, X., Muselet, D., Tremeau, A.: Color texture classification across illumination changes. In: Conf. on Colour in Graphics, Imaging, and Vision, pp. 332–337 (2010)