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Directional Rank Coding For Multi-scale Texture Classification

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Abstract. In this paper, we propose the Local Directional Rank Coding (LDRC) method for multi-scale texture classification. The LDRC is built from an extended notion of local extrema gray level. The LDRC collects directional information representing the rank order of the central pixel gray level calculated in four principal orientations in 3×3 neighborhood pixel. The four ranks are combined to get the final code. The LDRC produces 81 patterns. Multi-scale LDRC is calculated by altering the window size around a central pixel but the number of samples is restricted to eight neighbors by local averaging. So, the number of bins in a single scale LDRC histogram is kept small and constant. The proposed LDRC is evaluated on representative texture databases. The LDRC achieves good performance highly comparable to a recent state-of-the-art LBP variants.

1 Introduction

Texture classification is an active research topic in computer vision and pattern recognition. Typical applications include medical image analysis [1], industrial inspection [2], image retrieval [3], face recognition [4] and so on. Texture is often associated to several intuitive properties such as coarseness, contrast and regularity. But there is still no unique mathematical definition of texture that is consistent with perceptual properties of the human visual system [5]. There are many methods proposed for texture analysis, and can be classified in four general groups [5] i.e., structural methods, model based methods, filters based methods and statistical methods. The first group of texture analysis uses structural features of images. These methods decompose textures into elements known as primitives. The primitives and their spatial arrangement are used to characterize textures [6]. The second class of texture methods defines textures as probability models. Some well-known are Markov random field (MRF) [7], autoregressive (AR) model [8] and Gibbs random field [9]. The third approach to analyze textures applies filters on images such as Wavelet transform and Gabor filters [10-12]. The fourth and the last approach use statistical features. The main motivation behind these methods is based on the fact that the human visual system uses statistical features to distinguish textures [5]. Gray

level co occurrence matrixes are one of the earliest methods for texture feature extraction proposed by Haralick and al. [13]. Since then, it has been widely used in many texture analysis applications and remained to be important feature extraction method in the domain of texture analysis [14]. More recently, Ojala and al. developed a simple and efficient texture descriptor based on the local binary pattern (LBP) [15-16]. The LBP is based on the sign of the difference between the central pixel and its neighboring set of pixels. To improve the discriminative capability of LBP, many variants of LBP were recently proposed. Guo et al. [17] proposed the Local Binary pattern Variance (LBPV) that uses the variance as an adaptative weight in LBP. Lio et al [18] exploited the dominant LBP (DLBP) which uses the most frequently occurred patterns to capture descriptive textural information. In [19], Tan and al proposed Local Ternary Patterns (LTP) which encodes the pixel difference into 3 valued codes using a fixed threshold. Khellah [20] proposed a dominant Neighborhood Structure (DNS) method which fused the local LBP with global rotation-invariant features extracted from the generated image dominant neighborhood structure. Guo et al [21] suggested the Completed LBP (CLBP) that incorporates both the sign and magnitude of local differences. Liu et al. [22] proposed Binary Rotation Invariant and Noise Tolerant Texture Classification (BRINT) based on CLBP but using a new strategy for multi-resolution study. Hafiane et al. [23] propose Median Binary pattern (MBP) using the local median instead of the central pixel. Feiniu [24] proposed high order Derivative Local Binary Pattern (DLBP) by encoding the sequential binary values of high order directional derivatives.

The LBP variants are based on the development of different sampling patterns to capture the characteristics of certain textures. In this paper, we propose the Local Directional Rank Coding (LDRC) method. The LDRC is built from an extended notion of local extreme gray level [25], [26] in order to draw out some typical texture Patterns.

The LDRC is based on the sign of the difference between the central pixel and its neighboring such as LBP but the LDRC is able to collect directional information representing the rank order of the central pixel gray level calculated in four orientations in 3×3 neighborhood pixel. The four ranks are combined to get the final code. The LDRC operator produces 81 compact and discriminative features.

For multi-resolution study, LDRC feature Histogram is concatenated over multiple scales. To limit the growth in histogram bins with scale, the number of neighbors is restricted to be a multiple of eight by local averaging. This strategy produces a histogram feature of constant dimensionality of any scale.

The paper is organized as follows: section 2 describes the LDRC method; Section 3 presents the experimental results. Finally, section 4 concludes this paper.

2 Local Directional Rank Coding

For this encoding, we use a series of neighborhood composed of four elements. Each element is defined by a central pixel x and two aligned adjacent pixel surrounding it in a particular directions. This suite sweeps the four main directions 0° , 45° , 90° and 135° . For each direction, the three neighboring pixels are classified in order of their

gray levels .We assign the highest rank to the central pixel in the ordered list as shown in Fig.1.

The detailed explanation of θ° direction calculation is given as follows: Let x be the central pixel, p_i ($i= 1,2$) are its two surrounding pixels according to θ° direction. $I(x), I(p_i)$ are their corresponding gray values .

$$Cod_\theta(x) = \sum_{i=1}^2 F(I(x), I(p_i)); \quad \theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ \quad (1)$$

$$F(a, b) = \begin{cases} 1, & a - b \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

Similarly, the codes from the four orientations are calculated. Thus, for each one, the value associated to the central pixel is between 0 and 2. To find the final code, the string of ternary code $(cod_{135}cod_{90}cod_{45}cod_0)_3$ representing the fourth values calculated in the four directions is converted into its decimal equivalent according to equation (3). Also, the LDRC operators produces only 81 (3^4) patterns.

$$LDRC(x) = cod_0 \times 3^0 + cod_{45} \times 3^1 + cod_{90} \times 3^2 + cod_{135} \times 3^3 \quad (3)$$

The LDRC encoding procedure is illustrated in Fig. 1. The gray level of the central pixel is classed in the four directions according to equation 1 and 2. For example the rank of the central pixel in the horizontal direction is equal to 0 ($cod_0=0$), on other side, for the diagonal direction (135°), its rank is equal to 2 ($cod_{135}=2$), and the final label corresponding to LDRC will be 69.

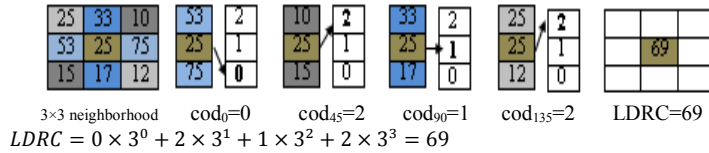


Fig. 1. Illustration of the basic LDRC

The LDRC represents an extended notion of local extrema gray level. If $Cod_\theta(x) = 0$, x represents the minimum gray level according to the direction θ , in contrast it represents the maximum gray level if $Cod_\theta(x) = 2$.So, the LDRC patterns bring directional extrema that is significant and important information for texture characterization.

The LDRC is invariant to monotonic gray level change, since the calculated code is based on the spatial interaction in the given locality; it does not depend on a fixed gray level value.

After computing the LDRC for each pixel (i, j), the whole image I is represented by building a histogram using equations 4 and 5.

$$H_{DLRC(l)} = \sum_{i=1}^{N1} \sum_{j=1}^{N2} f_r(LDRC(i, j), l) , l \in [0, L], \quad (4)$$

$$f_r(x, y) = \begin{cases} 1, & x = y \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

$N1 \times N2$ represent the size of texture image, L is the maximal DLRC code value.

3.1 Multi-Scale LDRC

For multi-resolution study, LDRC feature Histogram is concatenated over multiple scales. To limit the growth in histogram bins with scale, we proceed like strategy used in [22], however in LDRC the neighbors of the central pixel x are sampled on square neighborhood window of size $s \times s$.

So, the number of neighbors is restricted to be a multiple of eight, thus $P=8q$ for positive integer q :

$$\underline{x}_{s,8q} = [x_{s,8q,0}, \dots, x_{s,8q,8q-1}].$$

The neighbors' vector $\underline{x}_{s,8q}$ is transformed by local averaging to $\underline{y}_{s,q}$ such that the number of neighbors in $\underline{y}_{s,q}$ is always eight according to equation (6)

$$y_{s,q,i} = \frac{1}{q} \sum_{k=0}^{q-1} x_{s,8q,(qi+k)}, \quad i = 0, \dots, 7 \quad (6)$$

Fig.2 illustrates an example for transforming the original neighborhood $\underline{x}_{s,8q}$ into $\underline{y}_{s,q}$ according to equation (6), for example $y_{5,2,0} = \frac{x_{5,16,0} + x_{5,16,1}}{2}$

LDRC code is calculated for different spatial resolution by altering the window size $s \times s$. Given $\underline{y}_{s,q} = [y_{s,q,0}, \dots, y_{s,q,7}]$, LDRC is computing with respect to the central pixel for different scale accordingly to equations (1) and (2). LDRC feature Histogram is concatenated over multiple scales; it has $n \times 81$ dimensional features, n is the number of scales

3 Experimental Evaluation

3.1 Image Data and Experimental Set up

To evaluate the proposed method, we use three well-known comprehensive datasets : Brodatz [27], the Columbia-Utrecht Reflectance (CUREt) [28] and KTH-TIPS2 [29]. The dataset are summarized in table I, and described in detail in the following sections. Each texture image is converted into gray scale and normalized to zero mean and unit standard deviation.

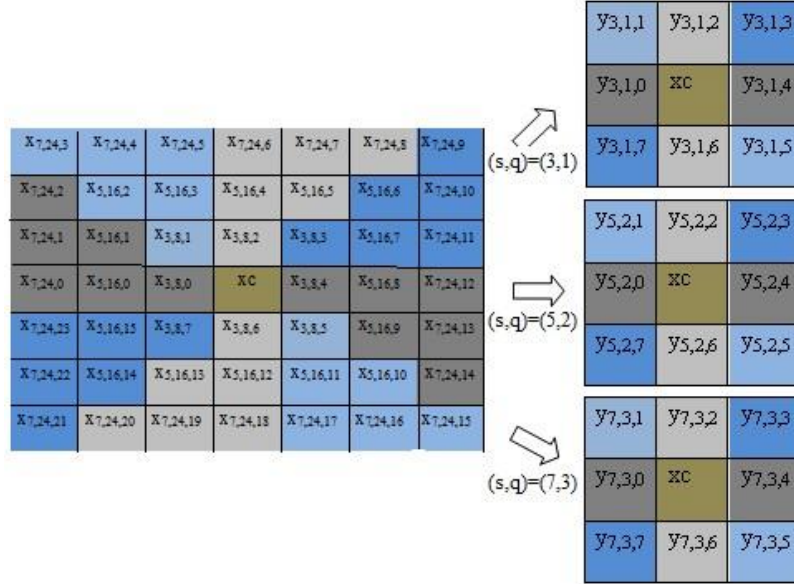


Fig. 2. Illustration of transforming original neighborhood . The different colors correspond to the 4 directional neighborhoods used in LDRC operator.

Table 1. Properties of three Data- set used in our Experiments

Dataset	Number of classes	Number of per classes	Total number of samples	Training samples per Class	Test samples per Class	Sample size (pixels)
Brodatz	24	25	600	13	12	64×64
CUReT	61	92	5612	46	46	200×200
KTH-TIPS2b	11	432	4752	324	108	200×200*

*Some samples are smaller than 200×200 pixels

The classification is performed using the Nearest Neighbor classifier (NNC) as in [20], [21], [22]. Therefore, a sample texture image will be assigned to the class corresponding to the nearest training model using the chi-square distance metric :

$$\chi^2(u, v) = \frac{1}{2} \sum_{i=1}^N \frac{(u_i - v_i)^2}{u_i + v_i} \quad (7)$$

Where N is the number of bins, u_i and v_i are respectively the values of the sample and model image at the i^{th} bin .

For multi-resolution analysis , LDRC feature Histogram is concatenated over nine scales by altering the window size from 3×3 to 19×19 .The concatenating features histogram is noted MS_n, n is the number of scales.

The proposed LDRC is compared with the dominant LBP (DLBP) [18], Dominant Neighborhood Structure (DNS)[20], Completed LBP (CLBP) [21] and BRINT [22].

3.2 Experimental results on the Brodatz database

We used the same subset of images which has been previously used in [18], [22]. There are 24 homogeneous texture classes extracted from Brodatz album (see Fig.3). Each texture image has the size of 640×640 pixels. Each texture image was partitioned into 25 no overlapping sub-images with the size of 128×128 , each of this was down sampled to the size 64×64 pixels. We selected 13 samples for training and the remaining 12 for testing. Results are reported over 100 random partitioning of the training and test sets. Then the average classification accuracies and standard deviations are calculated.

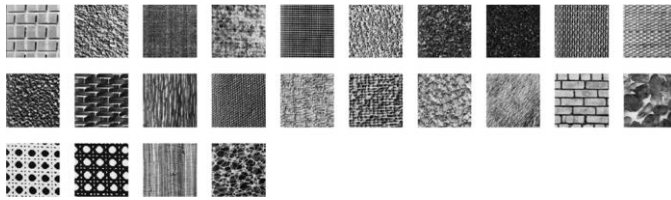


Fig. 3. 24 texture images from the Brodatz album.

Fig.4 plots the classification performance of LDRC as a function of number of scales. All the obtained results exceed 99%, but the best classification score is achieved using three scales (MS3).

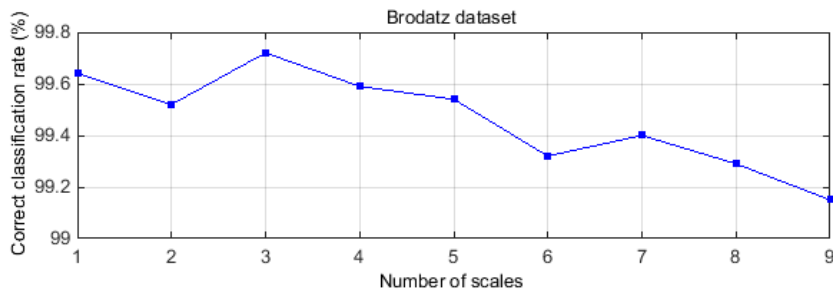


Fig. 4. LDRC Classification accuracies as a function of number of scales

Table 2 compares the classification performance of the proposed method with state of the art of texture classification methods. All the tested methods achieve very high classification. But CLBP features size is about 9 time the LDRC features size. Even BRINT performs the best with 100% accuracy, slightly exceeding our proposed method, it should be noted that the histogram features size of BRINT and LDRC are respectively 243(81*3) and 432 (144*3) what means that BRINT features size is about two times the feature size of LDRC. Also LDRC has low computational complexity. Based on the notion of extrema gray level, the LDRC patterns are discriminatives.

Table 2. Classification accuracies(%) achieved on Brodatz dataset

Methods	Classification rate(%)	Features size
DLBP+NGF[18]	99.54	K%
CLBP[21]	99.72±0.33	2200
BRINT[22]	100±0.00	432
LDRC(MS3)	99.72 ±0.32	243

3.3 Experimental results on the CURET database

The CURET database contains images of 61 materials as shown in Fig.6. Originally, the database contains 205 images for each texture class acquired at different viewpoints and illumination orientations. This makes the database far more challenging for a classifier than the often used Brodatz collection. We use the same subset of images which has been used in [20], [22]: 61 texture classes each with 92 images shot under varying illumination and a viewing angle of less than 60° but at constant scale. 46 images per class are randomly chosen for training and the remaining 46 per class are chosen for testing. The average classification accuracies and standard deviations are calculated over 100 random partitioning of the training and test sets.

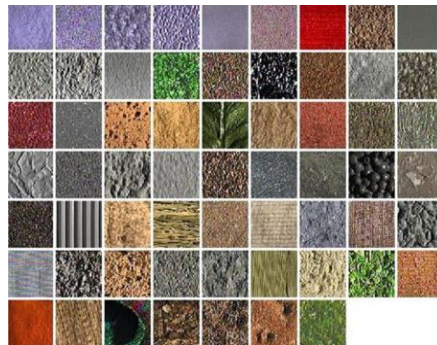


Fig. 5. The CURET dataset includes 61 different texture classes

Fig.6 plots the classification results as a function of scale. For the CURET data base the classification rate increase with number of scales, and the max is achieved with eight scales (MS8).

Table 3 lists the classification results of different methods. LDRC has the smallest features size and performs better than DLBP[18] , DNS[20],and CLBP [21] . BRINT is slightly more efficient then LDRC.

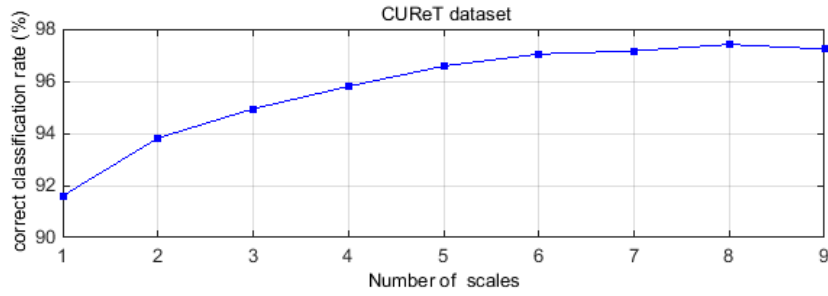


Fig. 6. Classification performance of the LDRC as a function of number of scales

Table 3. Classification accuracies(%) achieved on CURET dataset

Methods	Classification rate(%)	Features size
DLBP+NGF[18]	84.1	K%
DNS+LBP[20]	95.0	234
CLBP[21]	97.39	2200
BRINT[22]	97.86	648
LDRC(MS8)	97.41	648

2.4 Experimental results on the KTH-TIPS2b database

The KTH-TIPS2b dataset is another famous dataset created to address some of shortcomings of CURET dataset such as variation in scale and using different samples from the same material . KTH-TIPS2b dataset has 11 texture classes with 432 samples each. In each class, four objects have been imaged under nine different scales, four different illumination directions, and three different poses. Most samples are 200×200 pixels in size, but some are smaller due to scale issues. Fig.7 shows the texture classes in the KTH-TIPS2 dataset. We follow the training and testing scheme of [22] . In our experiment, only three samples are available during training, and testing is subsequently performed on all the remaining samples. Similarly, this experiment is also repeated four times by randomly selecting three different samples for training .The results are also reported as the average value over the four runs.



Fig. 7. The KTH-TIPS dataset includes 11 different texture classes

Fig.8 plots the classification performance as a function of number of scales. Similarly to other databases, the multi-resolution LDRC performs the classification rate. The best classification is reached for six scales (MS6).

The table 4 compares the best classification rates achieved by LDRC using six scales (MS6) with several recent state-of-the-art on KTH-TIPS2b database. BRINT is slightly more efficient than LDRC. But it should be noted that LDRC used only (81*6) features but BRINT is needed to 9*72 features [22].

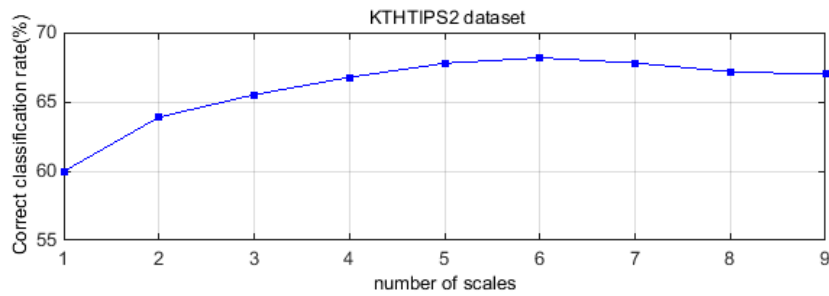


Fig. 8. Classification accuracies as a function of number of scales

Table 4. Classification accuracies(%) achieved on KTH-TIPS2 dataset

Methods	Classification rate (%)	Features size
DLBP+NGF[18]	49.3	K%
CLBP[21]	55.0	2200
BRINT[22]	69.6	648
LDRC(MS6)	68.18	486

2.5 Time execution

The experiments in this paper have been implemented on a PC with Intel i5 core, 4G RAM Windows 7 and Matlab version 8.4(2014b).The time elapsed to extract the 81 features from a texture image of size 200×200 is about 0.07 seconds.

2.6 Conclusion

We have presented the Local Directional Rank Coding (LDRC). It is a new thresholding and encoding schemes to create texture descriptors. This coding is built from an extended notion of local extreme gray level in order to draw out some typical texture Patterns. The LDRC combines directional information representing the rank order of the central pixel gray level calculated in four orientations in 3×3 neighborhood pixel. For multi-resolution study, LDRC feature Histogram is concatenated over multiple scales by altering the window size around a central pixel. To limit the growth in histogram bins with scale, the number of samples is restricted to eight neighbors by local averaging.

As demonstrated in the experimental results performed on three databases, LDRC is more efficient than well known LBP variants such as DLBP, DNS and CLBP, also it is highly comparable to BRINT. The proposed LDRC features have low computational complexity, powerful discriminative capability, and low sensitivity to illumination variation.

As future research, the proposed method can be applied to other classification problems such as face recognition and image retrieval.

References

1. Oliver, A., Freixenet, J., Mari, R., Pont, J., Pérez, E., Denton, E.R.E, Zwiggelaar, R. : A Novel Breast Tissue Density Classification Methodology. IEEE Transactions On Information Technology In Biomedicine 12(2008) 55-65
2. Xianghua, X. : A review of recent advances in Surface Defect Detection using Texture analysis. Techniques Electronic Letters on Computer Vision and Image Analysis Vol.7(2008)1-22
3. Subrahmanyam, M., Maheshwari, R.P., Balasubramanian, R.: Local maximum edge binary patterns: A new descriptor for image retrieval and object tracking. Signal Processing Vol.92(2012) 1467-1479
4. Dong-Rui, L. : Oriented Changing Light Facial Image Recognition Based on Sub Pattern Texture Analysis. International Journal of Signal Processing, Image Processing and Pattern Recognition Vol.8 (2015), 141-154
5. Tuceryan, M., Jain, A.K.: Texture analysis: Handbook of pattern Recognition and Computer Vision, 2nd ed. World Scientific Publishing, (1998)207-248
6. Zhang, J., Tan, T : Brief review of invariant texture analysis methods. Pattern recognition Vol.35(2002)735-747
7. Cohen, F.S., Fan, Z., Patel, M.A.: classification of rotated and scaled textured image using Gaussian markov random field models. IEEE Trans. Pattern Anal. Mach. Intell., Vol. 13(1991)192-202
8. Mao, M., Jain, A.K.: Texture classification and segmentation using multiresolution simultaneous autoregressive model. Pattern recognition Vol. 25(1992)173-188

9. Versteegen,R.,Gimel'farb,G.,Riddle,P.:Texture modelling with nested high-order Markov-Gibbs random fields.Computer Vision and Image Understanding Vol.143(2016)120-134
10. Bovik,A.C, Clark,M. ,Geisler,W.S. :Multiresolution texture analysis using localized spatial filters .IEEE.Trans.Pattern Anal.Mach.Intell.Vol.12(1990)55-73
11. Bianconi ,F., Fernandez,A.: Evaluation of the effects of Gabor filter parameters on texture classification. Pattern Recognition Vol.40(2007) 3325-3335
12. Ahmadvand, A. , Daliri, M.R. : Invariant texture classification using a spatial filter bank in multi-resolution analysis. Image and Vision Computing.Vol. 45(2016) 1-10
13. Haralick,R.M , Shanmugam,K. ,Dinstein I. :Textural features for image classification . IEEE Trans.Syst.Man Cyber.Vol.3(1973)610-621 .
14. Fernando Roberti de Siqueira , William robson Schwartz , helio pedrini : Multi-scale gray level co -occurrence matrices for texture description . Neurocomputing 120(2013)336-34
15. Ojala,T ,Pietikainen,M. ,Harwood,D. :A comparative study of texture measures with classification based on features distributions .Pattern Recognition .Vol.29(1996)51-59
16. Ojala,T ,Pietikainen,M. ,Maenpaa,T.: Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence .Vol.24(2002)971-987
17. Guo,Z., Zhang, L. , Zhang,D. :Rotation invariant texture classification using LBP Variance (LBPV) with global matching .Pattern Recognition Vol.43(2010) 706 -719
18. Liao,S. ,Law, Max W .K. , Chung, Albert C.S. : Dominant Local Binary Patterns for Texture Classification. IEEE Transactions on Image Processing .Vol.18(2009) 1107-1117
19. Tan,X. , Triggs,B.: Enhanced local texture features sets for face recognition under difficult lighting conditions. IEEE Transactions on Image processing .Vol .19(2010) 1635-1650
20. Khellah,F.M:Texture Classification Using Dominant Neighborhood Structure. IEEE Tran. Image Process. Vol.20(2011) 3270-3279
21. Guo,Z, Zhang,L. , Zhang,D. : A completed modeling of local binary pattern operator for texture classification. IEEE Tran. Image Process.Vol.9(2010)1657-1663
22. Liu,L. , Long,Y., Fieguth.P., Lao,S. , Zhao,G. :BRINT: Binary Rotation Invariant and Noise Tolerant Texture Classification. IEEE transactions on Image Processing, Vol .23(2014)3071-3084
23. Hafiane A., Palaniappan K. , Seetharaman G., Median Binary Patterns for texture classification. Pattern Recogn.Vol.48(2015)2609-2620
24. Feiniu, Y: Rotation and scale invariant local binary pattern based on high order directional derivatives for texture classification. Digital Signal Processing 26 (2014) 142-152
25. Ouslimani,F, Ameer.Z , Ouslimani,A. :Texture analysis method using regional rank coding. CSNDSP 2014, 353-356
26. Ouslimani, F.,Ouslimani,A, Ameer,Z.: Noise-robust texture features using local directional rank coding , Advances in Computer Science and Engineering,Vol. 15(2015) 1 - 12
27. Brodatz,P.: Textures: A Photographic Album for Artissts and Designers ,Dover Publications,New York,1966.
28. Dana K., Van-Ginneken B., Nayar S. and Koenderink J.: Reflectance and texture of real world surfaces, ACM Trans.Graph.,18-34 (1999), <http://www.cs.columbia.edu/CAVE//exclude/curet/>
29. Mallikarjuna P. ,Fritz M., Targhi A.T. , Hayman E., Caputo B. and Eklundh J. , The KTH-TIPS2 Databases, <http://www.nada.kth.se/cvap/databases/kth-tips/>