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An Efficient BRINT-Random Forests Algorithm Based Texture Classification

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Abstract: Texture analysis is considered fundamental and important in the field of pattern to computationally represent an intuitive perception of texture and to facilitate automatic processing of the texture information for artificial vision systems. The texture classification methods based on local binary patterns (LBP),Scale Invariant Feature Transform(SIFT),Binary Rotation Invariant And Noise Tolerant Texture Classification (BRINT), Nearest Neighborhood Classifier(NNC) etc. performs texture classification with accuracy the need of high training samples and increased time consumption are the major challenges. In this paper, random forest algorithm is used to deal with the problem of texture classification. The proposed classifier consists of a number of trees, with each tree grown using some form of randomization. The leaf nodes of each tree are labeled by estimates of the posterior distribution over the image classes. Each internal node contains a test that best splits the space of data to be classified. Time consumption can be reduced considerably because of this random forest Algorithm. The proposed algorithm is having high accuracy with less time consumption.

Keywords: LPB, SIFT, BRINT-NNC Classifier.

I. INTRODUCTION

Although there is no strict definition of the image texture, it is easily perceived by humans and is believed to be a rich source of visual information – about the nature and three dimensional shape of physical objects. Generally speaking, textures are complex visual patterns composed of entities, or subpatterns that have characteristic brightness, colour, slope, size, etc. Thus texture can be regarded as a similarity grouping in an image (Rosenfeld 1982). The local sub pattern properties give rise to the perceived lightness, uniformity, density, roughness, regularity, linearity, frequency, phase, directionality, coarseness, randomness, fineness, smoothness, granulatin, etc., of the texture as a whole (Levine 1985). For a large collection of examples of textures are included in (Brodatz 1966).

Feature extraction is the first stage of image texture analysis. Results obtained from this stage are used for texture discrimination, texture classification or object shape determination Approaches to texture analysis are usually categorized into structural, statistical, Model based, transform methods. Structural approaches (Haralick 1979, Levine 1985) represent texture by well-defined primitives (microtexture) and a hierarchy of spatial arrangements (macrotexture) of those primitives. To describe the texture, one must define the primitives and the placement rules. The choice of a primitive (from a set of primitives) and the probability of the chosen primitive to be placed at a particular location can be a function of location or the primitives near the location. The advantage of the structural approach is that it provides a good symbolic description of the image; however, this feature is more useful for synthesis than analysis tasks. The abstract descriptions can be ill defined for naturaltextures because of the variability of both micro- and macrostructure and no clear distinction between them. A powerful tool for structural texture analysis is provided by mathematical morphology. It may prove to be useful for bone image analysis, e.g. for the detection of changes in bone microstructure.

As humans, it is simple (even for a child) to identify letters, objects, numbers, voices of friends etc. However, to solve these types of problems is a very complex task. Pattern recognition is the science with the objective to classify objects into different categories and classes. It is a primary component of artificial intelligence and computer vision. Pattern recognition methods are used in various areas such as science, engineering, business, medicine and etc.. Texture can be broadly defined as the visual or tactile surface characteristics and appearance of something. Texture is an important characteristic for analysis of many types of images. Texture is present in many real as well as artificial data e.g. clouds, trees, wood, hair, fabric etc. Even though its importance and present everywhere in image data a formal approach or definition of texture

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analysis does not exist. Texture is a natural property of almost all surfaces the grain of wood, the weave of fabric, the pattern of crop in fields etc. It contains important information about the structural arrangement of surfaces and their relationship to the surrounding environment

The texture classification problem is conventionally divided into the two subproblems. It is generally agreed that the extraction of powerful texture features is of more importance to the success of texture classification and, consequently, most research in texture classification focuses on the feature extraction part. Nevertheless it remains a challenge to design texture features which arecomputationally efficient, highly discriminative and effective, robust to imaging environment changes (including changes in illumination, rotation, view point, scaling and occlusion) and insensitive to noise Recently, the Bag-of-Words (BoW) paradigm, representingtexture images as histograms over a discrete vocabulary oflocal features, has proved effective in providing texture features [2]–[7].

Within the BoW framework, the focus of attention has been on the design of local texture descriptors capable of achieving local invariance [2], [4]–[7]. These descriptors can be classified as dense or sparse, with the sparse approaches, such as SPIN, SIFT and RIFT [4], [10], requiring a process of detecting salient regions before applying the texture descriptors, leading to issues of implementation and computational complexity and instability. In contrast, dense approaches, applying texture descriptors pixel by pixel are more popular. Important dense textures descriptors include Gabor wavelets [8], LM filters [5], MR8 filters [5], BIF features [7], LBP [2], Patch descriptor [6] and RP random features [3] and many others [4].

Among local texture descriptors, LBP [2], [11] has emerged as one of the most prominent and has attracted increasing attention in the field of image processing and computer vision due to its outstanding advantages: (1) ease of implementation, (2) no need for pre-training, (3) invariance to monotonic illumination changes, and (4) low computational complexity, making LBP a preferred choice for many applications. Although originally proposed for texture analysis, the LBP method has been successfully applied to many diverse areas of image processing: dynamic texture recognition, remote sensing, fingerprint matching, visual inspection, image retrieval, biomedical image analysis, face image analysis, motion analysis, edge detection, and environment modeling [12]–[17]. Consequently many LBP variants are present in the recent literature.Although significant progress has been made, most LBPvariants still have prominent limitations, mostly the sensitivity to noise [19], [21], and the limiting of LBP variants to three scales, failing to capture long range texture information [19], [21], [23]. Although some efforts have been made to include complementary filtering techniques [21], [24], these increase the computational complexity, running counter to the computational efficiency property of the LBP method.

In this paper, computationally simple approach, the Binary Rotation Invariant and Noise Tolerant (BRINT) descriptor, which has the following outstanding advantages: It is highly discriminative, has low computational complexity, is highly robust to noise and rotation, and allows for compactly encoding a number of scales and arbitrarily large circular neighborhoods. At the feature extraction stage there is no pre-learning process and no additional parameters to be learned. The texture classification is done on the basis of Random Forest Algorithm. An image is classified by sending it down every tree and aggregating the reached leaf distributions. Random forest is an ensemble classifier that consists of many decision trees and outputs the class that is the mode of the class's output by individual trees. The method combines Breiman's "bagging" idea and the random selection of features. The decision tree classifiers are popular due to their intuitive appeal and easy training procedures. The underlying nature of random forest is that of building classifiers independently. Random forest can be constructed parallelly, and gives flexibility to exploit parallel computing architectures.

The Random forest method of texture classification first extracts the texture using BRINT (binary rotation invariant and noise tolerant) feature extraction method. This feature extraction method performs well when compared to the conventional LBP, a small set of most discriminant texture features extracted using BRINT method. Only this small set of discriminant features is used to classify the images. In a randomized tree the split at each node happens by using only a randomly selected subset of all the features. The texture images are classified accordingly. The proposed method is having high accuracy with reduced time consumption. The resulting system is fast and accurate with less time consumption

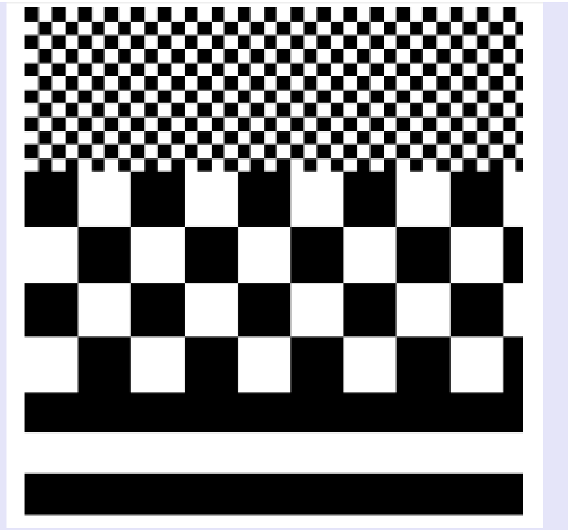

Figure 1.1 Texture Pattern

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II. FEATURE EXTRACTION

First we need to determine the features of a given input image the brint method is used for the feature extraction.

A.BRINT_S

1) BRINT S descriptor: The construction of the local BRINT S descriptor is illustrated in Fig. 2.1 Similar to the samplingscheme in the original LBP approach, we sample pixels around a central pixel,x_c however on any circle of radius r,here restrict the number of points sampled to be a multiple ofeight.

$$BNT\_S=\sum s(y_{r,q,p}-x_c)2^n \qquad n=0,\dots 7 \quad (2.1)$$

Given $y_{r,q}=[y_{r,q,0},\dots\dots y_{r,q,7}]^T$,the BRINT_S features can be calculated.

B.BRINT_M

2) BRINT M descriptor :Motivated by the striking classificationresults achieved by BRINT S and considering thebetter performance of the CLBP CSM feature over the singlefeature LBP proposed by Guo.Given center pixel x_c, the neighbouring pixels $x_{r,p,0},\dots x_{r,p,p-1}$ first compute absolute difference between local neighbours and its central pixel.

$$BNT\_M=1/q\sum\Delta_{r,8q,(qi+k)} \quad i=0,1,\dots 7k=0,..q-1 \quad (2.2)$$

Where

$$\Delta_{r,8q}=|x_{r,8q,i}-x_c|, \quad i=0,\dots 8q-1 \quad (2.3)$$

C.BRINT_C

2) BRINT C descriptor:Finally represent the central pixel in one of two bins

$$BNT\_C=8(x_c-\Phi_{I,r}) \qquad (2.4)$$

where $\Phi_{I,r}=1/(M-2r)(N-2r)\sum_i\sum_j x(i,j)$ i=r+1 to M-r, j=r+1 to N-r .

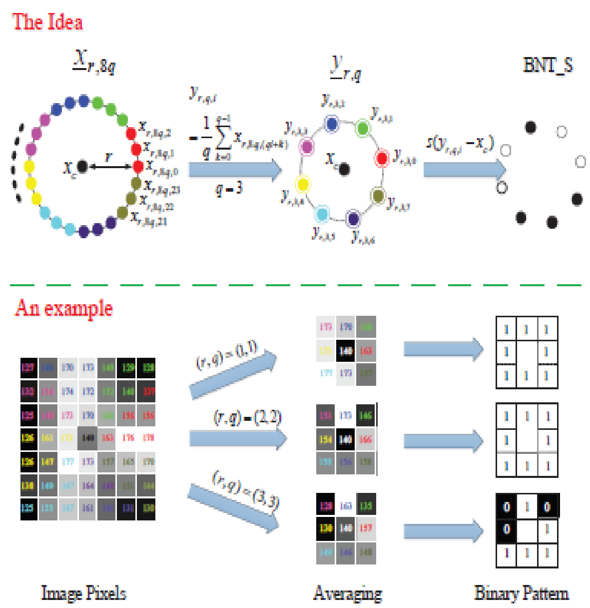

Fig:2.1 Illustration of BNT_S descriptor

The overall frame work of thebrint method of texture feature extraction is explained on the fig 2.2.The BNT_S, BNT_M, BNT_C features are combine together to obtain the desired texture features. The extracted features are further used for the final texture classification using the proposed Random forest algorithm method.

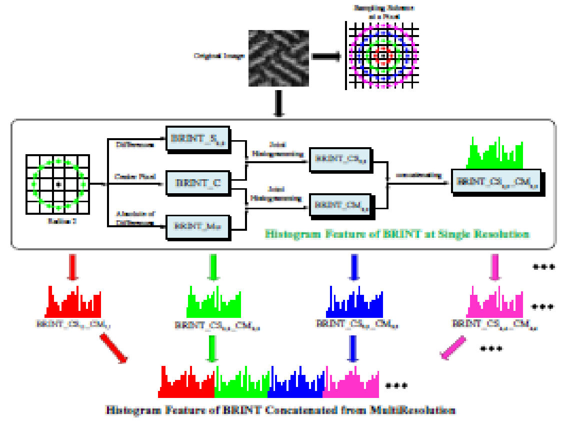

Fig2.2: Overall Frame work of BRINT texture feature extraction method

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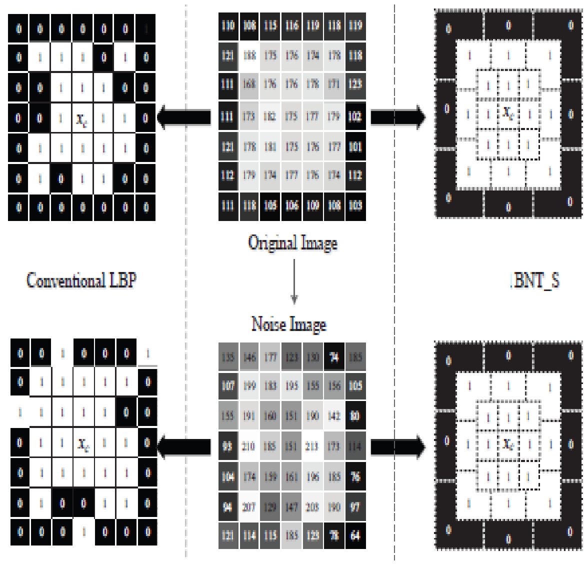

Figure 2.2: Illustration of BNT_S approach

The BRINT method of texture feature extraction method helps in reducing the memory requirements by reducing the number of histograms since the different features are concatenated to obtain the required histogram feature values. The features thus obtained are further used for the proposed Random forest algorithm method of texture classification.

III. CLASSIFICATION USING RANDOM FORESTS ALGORITHM

A. RANDOM FORESTS ALGORITHM

A supervised learning system is characterized by a learning algorithm and a labeled training data. The

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algorithm dictates the process of learning from information extracted from the training data. A Random tree is structurally homogeneous to classical decision trees Random trees are grown recursively from top to down. Random decision trees randomize the decision criteria. With regards to a random forest classifier there are two parameters:

Forest Size (n_{tree}): This specifies number of trees to be grown. Increasing the number of trees increases the generalization accuracy. The increase in accuracy is at the cost of an increased training and classification time. In this paper random forest of range of about 100-1000 trees are grown.

Test size (m_{try}): This specifies number of variables used to determine the best split at the node. Let the node at which we are starting be called the **initial node**. The Random Forests Algorithm can be summarized as follows.

1. Draw n_{tree} bootstraps samples from the original data.
2. For each of the sample grow an unpruned classification of regression tree at each node randomly sample $m_{try}$of the predicators and choose the best split among those variables.
3. Predict the new data by aggregating the predictions of n_{trees},

Summarizing the random forests is creating a large number of independently trained classifier.

Algorithm:

Requires: Training images, D= $\{\Gamma_N, CP\}$; N=1…n;P=1…p
1: let the current node be t
2: ifΓ_t contains image from only one class or a stopping condition is reached
Then
3: return the value of t
4: **else**
5: Choose a **test** $T_t=\{f_t , \Gamma_l, \Gamma_r \}$
6: splitΓ_t as Γ_l,Γ_r , such that , $\Gamma_l u \Gamma_r = \Gamma_t$
7: Return t
Algorithm for choose a test
1: $|\Gamma_t| \geq 0$
2: For each image do
3: If $f_t > \Phi_t$ then do
4: Group the image on Γ_r
5: else
6: Group the image on Γ_r
7: End for
8: Calculate the decrease in giniimpurity, Δ_i
9: **End for**
10: Return the value with less gini impurity

The algorithm thus classifies the texture features accordingly. Time consumption can be reduced considerably because of this Random Forests Algorithm.

IV. SIMULATION RESULTS

The Random Forests agorithm is simulated using Matlab and the results shows that the time consumption made reduced considerably when compared with the coventional NNC classifier. Here, about 500 iterations has been taken and found that the latency get reduced. The figure 4.1to 4.5 shows the BRINT texture feature extraction output. Figure 4.6 shows the final classified output of BRINT random forest classifier.

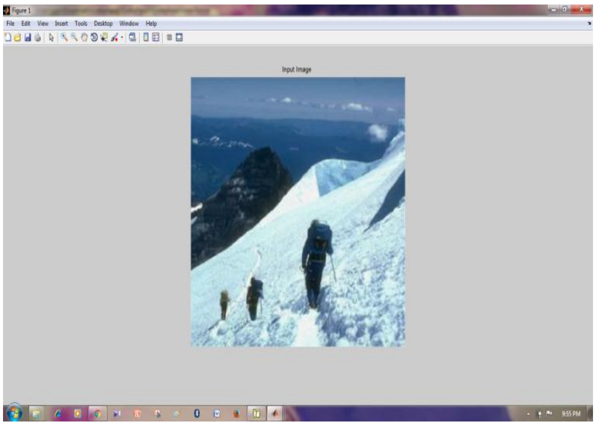

Figure 4.1 The input image to the proposed BRINT random forest classifier.

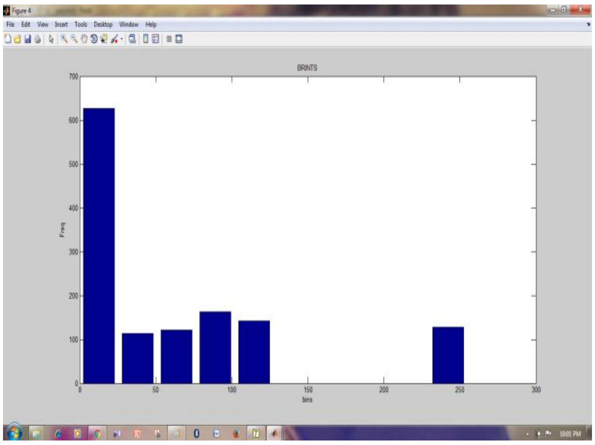

Figure 4.2 The BNT_S feature extraction output

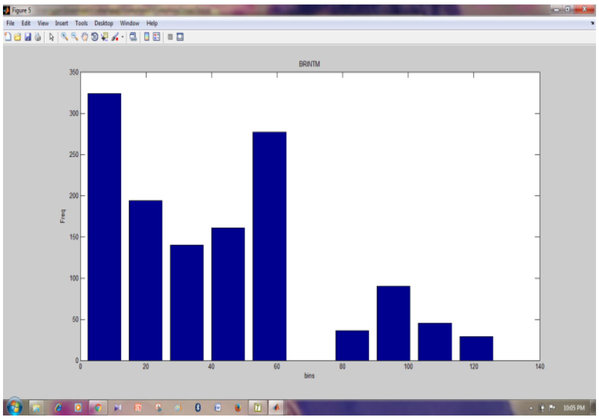

Figure 4.3 The BNT_M feature extraction output

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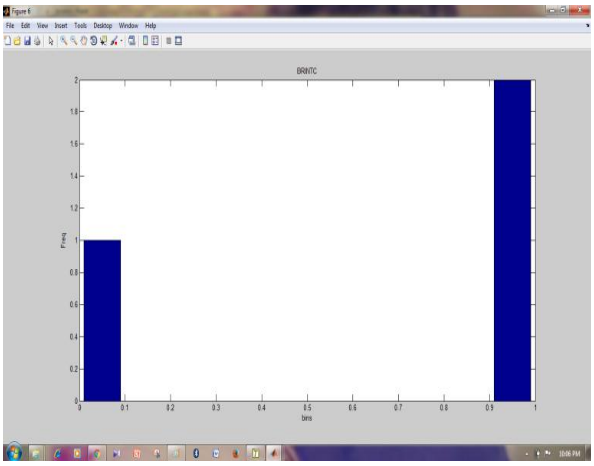

Figure 4.4 The BNT_C feature extraction output

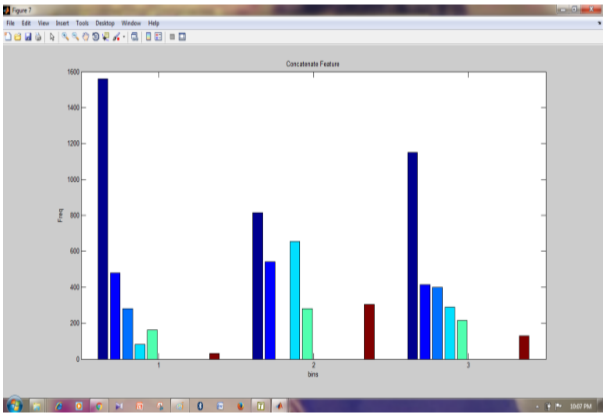

Figure 4.5 The concatenated Feature extraction output

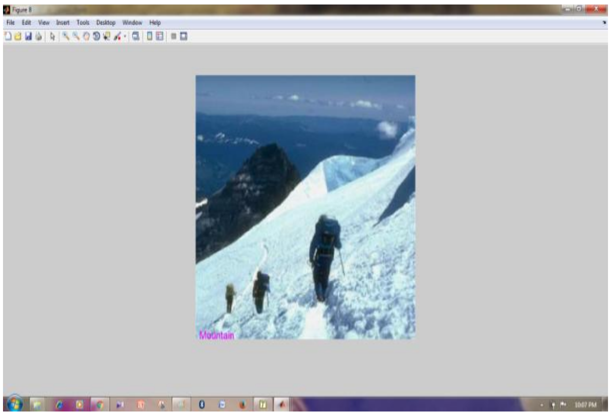

Figure 4.6 The classified output

V. COMPARISON

The comparison of the proposed BRINT random forest classifier with the existing BRINT NNC classifier method is done and the results are tabulated. Fig 5.1 shows the time consumption analysis of the proposed method with the existing method. Fig 5.2 shows the comparison of accuracy. The fig 5.3 shows the graphical analysis of proposed BRINT random forest texture classifier with the existing BRINT NNC classifier. The proposed method gives high accuracy with less time consumption.

Classifier	Trial 1(sec)	Trial 2(sec)	Trial 3(sec)	Overall
NNC(BRINT)	0.8	1.2	1.4	1.09
Random Forest Brint	0.71	0.94	0.94	0.78

Figure 5.1The time consumption analysis

Classifier	Trial 1	Trial 2	Trial 3	Overall (%)
NNC (BRINT)	94.04	92.20	92.42	93.62
Random Forest Brint	93.33	94.10	93.21	93.33

Figure 5.2 comparison of accuracy analysis

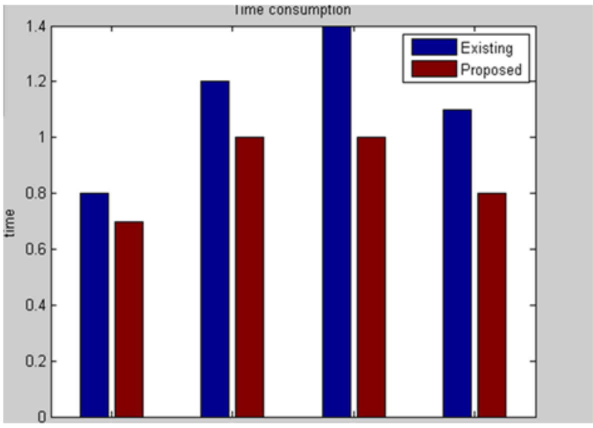

Figure 5.3The time consumption analysis with the proposed and existing method.

VI. CONCLUSION AND FUTURE WORK

This paper proposed random forest algorithm for texture classification. The aim of this work is to present a modified algorithm for the texture classification method to achieve improved performance in terms of accuracy and time consumption. The proposed algorithm is the slight variation from the NNC classifier method. The future scope lies in the use of the proposed BRINT random forest texture classifier in applications like biometric systems including face recognition systems. Regarding the proposed mechanism, the simulations presented in this paper clearly show the efficiency of the technique, which can aid in texture classification faster than the non-reliable one.

REFERENCES

[1] X. Xie, M. Mirmehdi, A galaxy of texture features. In: M. Mirmehdi, X. Xie, J. Suri (eds.) Handbook of texture analysis, Imperial College Press (2008), pp. 375–406.

[2] T. Ojala, M. Pietik¨ainen, and T. M¨aenp¨a¨a, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 7, pp. 971-987, Jul. 2002.

[3] L. Liu, and P. Fieguth, "Texture classification from random features," IEEE Trans. Pattern Anal. Mach. Intell., vol. 34, no. 3, pp. 574-586, March 2012.

[4] J. Zhang, M. Marszalek, S. Lazebnik and C. Schmid, "Local features and kernels for classification of texture and object categories: a comprehensive study," Int. J. Comput. Vision, vol. 73, no. 2, pp. 213-238, 2007.
[5] M. Varma and A. Zisserman, "A statistical approach to texture classification from single images," Int. J. Comput.Vision, vol. 62, no. 1-2, pp. 61–81, 2005.
[6] M. Varma and A. Zisserman, "A statistical approach to material classification using image patches," IEEE Trans. Pattern Anal. Mach. Intell., vol. 31, no. 11,pp. 2032-2047, Nov. 2009.
[7] M. Crosier and L. D. Griffin, "Using basic image features for texture classification,"Int. J. Comput.Vision, vol. 88, pp. 447–460, 2010.
[8] B.S. Manjunathi, and W.Y. Ma, Texture Features for Browsing and Retrieval ofImage Data, IEEE Trans. Pattern Anal. Mach. Intell., vol. 18, no. 8, pp. 837–842,1996.
[9] L. Liu, B. Yang, P. Fieguth, Z. Yang and Y. Wei, "BRINT: A binary rotationinvariant and noise tolerant texture descriptor," in IEEE International Conferenceon Image Processing (ICIP), pp. 255–259, 2013.
[10] S. Lazebnik, C. Schmid, and J. Ponce, "A sparse texture representation usinglocal affine regions," IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 8, pp.1265–1278, Aug. 2005.
[11] T. Ojala, M. Pietik¨ainen, D. Harwood, "A comparative study of texture measureswith classification based on feature distributions", Pattern Recognit., vol. 29, no.1, pp. 51–59, 1996.
[12] A. Ferna´ndez, M. A´ lvarez and F. Bianconi, "Texture description through histogramsof equivalent patterns", J. Math.Imaging Vis., vol. 45, no. 1, pp. 76–102, January 2013.
[13] D. Huang, C. Shan, M. Ardabilian, Y. Wang, and L. Chen, "Local binary patternsand its application to facial image analysis: a survey", IEEE Trans. Syst. ManCybern C Appl. Rev., vol. 41, no. 6, pp. 765–781, 2011.
[14] M. Heikkil¨a, M. Pietik¨anen and C. Schmid."Description of interest regions withlocal binary patterns", Pattern Recognit., vol. 42, no. 3, pp. 425–436, 2009.
[15] Y. Guo, G. Zhao, and M. Pietik¨ainen, "Discriminative features for texturedescription", Pattern Recgnit., vol. 45, pp. 3834–3843, 2012.
[16] M. Teutsch, and J. Beyerer, "Noise resistant gradient calculation and edgedetection using local binary patterns", in: Asian Conference on Computer VisonWorkshop, J.J. Park and J. Kim (Eds), LNCS 7728, pp. 1-14, 2013.
[17] M. Paci, L. Nanni, A. Lahti, K. Aalto-Set¨al¨a, J. Hyttinen, and S. Severi, "Non-binary coding for texture descriptors in sub-cellular and stem cell image classification", Current Bioinformatics, vol. 8, pp. 208-219, 2013.
[18] A. Fathi and A.R. Naghsh-Nilchi, "Noise tolerant local binary pattern operator for efficient texture analysis", Pattern Recognit. Letters, vol. 33, no. 9, pp. 1093-1100, 2012.
[19] F.M. Khellah, "Texture Classification Using Dominant Neighborhood Structure,"IEEE Trans. Image Process., vol. 20, n0. 11, pp. 3270–3279, Nov. 2011.
[20] J. Ren, X. Jiang, and J. Yuan, "Noise resistant local binary pattern with anembedded error correction mechanism," IEEE Trans. Image Process., vol. 22,no. 10, pp. 4049-4060, 2013.
[21] S. Liao, Max W. K. Law, and Albert C. S. Chung, "Dominant local binarypatterns for texture classification," IEEE Trans. Image Process., vol. 18, no. 5,pp. 1107-1118, may, 2009.
[22] T. M¨aenp¨a¨a, M. Pietik¨ainen, "Multi-scale binary patterns for texture analysis",in Scandinavian Conference on Image Analysis (SCIA), pp. 885–892, 2003.
[23] T. Ahonen, J. Matas, C. He, and M. Pietik¨ainen, "Rotation invariant image description with local binary pattern histogram Fourier features," in Scandinavian Conference on Image Analysis (SCIA), pp. 61–70, 2009.
[24] Z. Guo, L. Zhang and D. Zhang, "A completed modeling of local binary pattern operator for texture classification", IEEE Trans. Image Process., vol. 9, no. 16,pp. 1657–1663, 2010.