

Diamond Sampling Structure based BRINT Descriptor for Texture Classification

Bala Sandeep Vallabhaneni¹, S. Srinivas Kumar²

¹M.Tech Scholar, ²Professor,

Department of Electronics and Communication Engineering,

UCEK(A), JNTUK, (India)

ABSTRACT

The problem of texture classification is discussed in this paper. Local Binary Patterns (LBP) and most of LBP variants still suffer from high noise sensitivity, high dimensionality and computational complexity. An approach in which points are sampled in a diamond like structure is proposed and fixing the number of neighbor samples to 8. This decreases the feature dimension significantly. The points are sampled in different neighborhoods and encoded over a number of scales. The sampling points are averaged along radial direction for robustness of noise. In addition, a new descriptor based on Binary Rotation Invariant and Noise Tolerant (BRINT) descriptor is created to extract features. Unlike BRINT, uniform rotation invariant patterns in place of rotation invariant patterns is used for each of the three descriptors. These three descriptors are added jointly to get proposed descriptor. The experimental results on two benchmark texture datasets (OUTEX_TC_12_000 and KTH-TIPS2b) prove that the proposed approach performs better than other state-of-the-art LBP variants both under noise free and noisy conditions. The proposed approach is tested under different noise environments of Gaussian, salt and pepper and speckle to demonstrate its robustness of noise.

Keywords: Diamond Sampling Structure, Local Binary Pattern (LBP), Low Complexity, SVM, Texture Classification

I INTRODUCTION

Texture is a basic feature of visual aspect in all naturally occurring surfaces. It is used in the area of image processing to extract visual information from textures. The texture information is useful in several pattern recognition and computer vision problems like object classification and face identification. Texture classification is one of the difficulties faced in texture analysis. The various applications of texture classification include analysis of medical image, document identification and remote sensing. The various problems faced by texture classification method are as follows: low texture variation between different texture classes, changes in illuminations, view point and scale. The above problems were not dealt consummately by prevailing techniques and need improvement. The above issue is addressed in this paper comprehensively.

Numerous approaches have been in use for the texture classification in the past two decades. The objective of different approaches is to create an appropriate representation of a texture which inscribe the information of

texture disregard for scale, rotation and lighting conditions. The different approaches of texture classification can be parted in two ways: Local Binary features and Bag of Words (BoW) paradigm. The BoW paradigm symbolize the image or texture as a histogram over discrete vocabulary of local features. Binary features gained popularity owing to its low complexity, effective and efficient performance. The original Local Binary Patterns (LBP) that is proposed by Ojala *et al.*[2] received wide spread recognition and popularity owing to the advantages as mentioned above. These advantages made LBP one of the best alternative for numerous uses relating to texture classification. Even though it has significant advantage over other methods, it is mainly intolerant to noise and fails to capture information from a large area.

The original LBP considers only the sign knowledge of difference between local pixels, then it encodes the difference sign into either 0 or 1. These codes are converted into a decimal number to depict arrangement. Pietkainen *et al.* [6] proposed a variation of LBP for rotation invariance to hold patterns which are rotationally unique there by reducing the feature dimension to 36. In addition, Ojala *et al.* [2] through their experiments found out that uniformity is the fundamental characteristic of textures and proposed uniform rotation invariant patterns of LBP. These patterns are calculated by taking bitwise transitions from 0 to 1 or 1 to 0 and considers only those patterns which has at most two bitwise transitions. Local Ternary Patterns (LTP) is proposed [3] as an extension of LBP to threshold pixels into three values and these three values are used to achieve lower and upper binary patterns. These two binary patterns are concatenated to get the descriptor that is better than LBP. Dominant LBP was proposed by Liao *et al.* [11] where only dominant patterns are considered. Guo *et al.* [4] proposed completed LBP (CLBP) considering both the magnitude and sign information pertaining to neighbor differences with the center pixel. Liu *et al.* [1] proposed BRINT descriptor for improved noise robustness and low feature by averaging pixels along an arc of circular neighborhood. BRINT restricts the number of neighbor pixels to 8 to improve noise robustness.

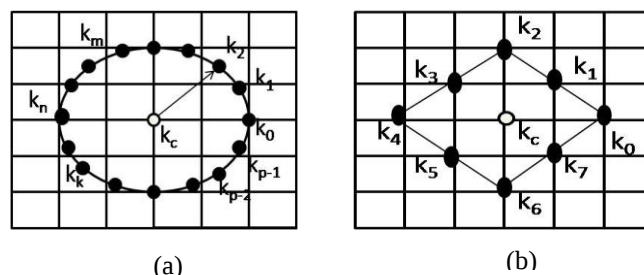


Fig. 1. (a) Circular sampling structure. (b) Diamond sampling structure.

The above mentioned LBP variants have drawbacks of high computational complexity, less discriminative capability and noise sensitivity. To overcome these shortcomings, diamond sampling structure proposed by Zhibin *et al.* [10] which samples the pixels along diamond like locus is used thus reducing computational complexity. In this structure, the number of neighbors are fixed to 8. Moreover, all the neighbor pixels are averaged in the direction of 8 neighbor pixels ahead of binarization to improve insensitivity of noise. Two benchmark datasets are used in the experimental surveys to show the improved performance of proposed approach over the other LBP variants. It is having low complexity, noise robustness while ensuring efficiency.

II THE PROPOSED APPROACH

2.1 A Diamond Sampling Approach

Generally, in LBP sampling structure pixels are sampled in a circular neighborhood as shown in Fig. 1 (a). The sign of difference between center pixel k_c and J neighbor pixels ($p=0,1,\dots,J-1$) situated on a circle of radius r is encoded to calculate LBP.

$$LBP_{r,J} = \sum_{i=0}^{J-1} s(k_p - k_c) 2^i, \quad s(a) = \begin{cases} 1, & a \geq 0 \\ 0, & a < 0 \end{cases} \quad (1)$$

In this structure, if any of the neighbor pixels does not fall in the center of pixels then it will be approximated using bilinear interpolation. These interpolation generates inaccurate pixel values and undependable pixel data. Moreover, dimensionality of features increases gradually with the increasing neighbor samples which increases computation time.

In order to subdue these defects, diamond sampling structure is used in which distance between central pixel and its neighbors utilize Manhattan distance to supersede circular symmetric neighborhood structure. In diamond sampling structure, all of the neighbor pixels sit at integer pixel positions.

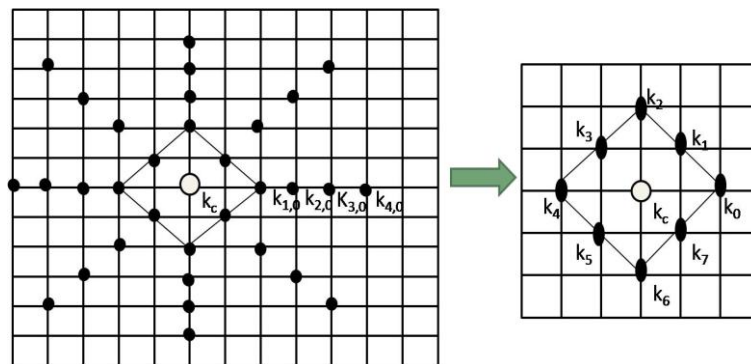


Fig. 2. Averaging method used in the proposed approach

The diamond sampling structure used in this paper is shown in Fig. 1 (b). The number of neighbor pixels is restricted to 8 to diminish feature dimension. A resolution of 9 with additional 8 samples at each resolution is utilized as used in the multi resolution analysis of circular sampling structure. All the neighbors in each resolution is averaged along 8 radial directions.

2.2 Averaging along radial direction

Averaging method in the direction of neighbor pixels is used to decrease the noise sensitivity which several LBP-like descriptors fails to achieve. Averaging method is used along the direction of 8 neighbor pixels for multi resolution analysis. Unlike original LBP, the neighbor pixel is replaced with the average of pixels along a radial direction, as shown in Fig. 2.

$$k_p = \frac{1}{m} \sum_{r=1}^m k_{r,p}, \quad (p = 0, 1, \dots, J-1) \quad (2)$$

Where $k_{r,p}$ is the pixel value of the r^{th} sample pixel direction of the given neighbor pixel k_p . Here 'm' depicts the resolution number or total count of pixels used in averaging and J represents the total number of neighbor

pixels. Here $J=8$ is used as number of pixels. We used multi-scale approach in this paper and 9 different scales to arrive at the desired descriptor. In Fig. 2, an illustration of averaging along radial direction is shown where four pixels are used to do average along all 8 radial directions.

2.3 DM_BRINT descriptor

BRINT descriptor approach is used to extract features as it has 3 descriptors to capture complementary information about texture. BRINT descriptor consists of 3 descriptors: BRINT_S, BRINT_M and BRINT_C. These three descriptors devised by taking motivation from CLBP. All the three descriptors of BRINT are used to effectively classify texture. Motivated by BRINT we create three new descriptors which are analogous to BRINT.

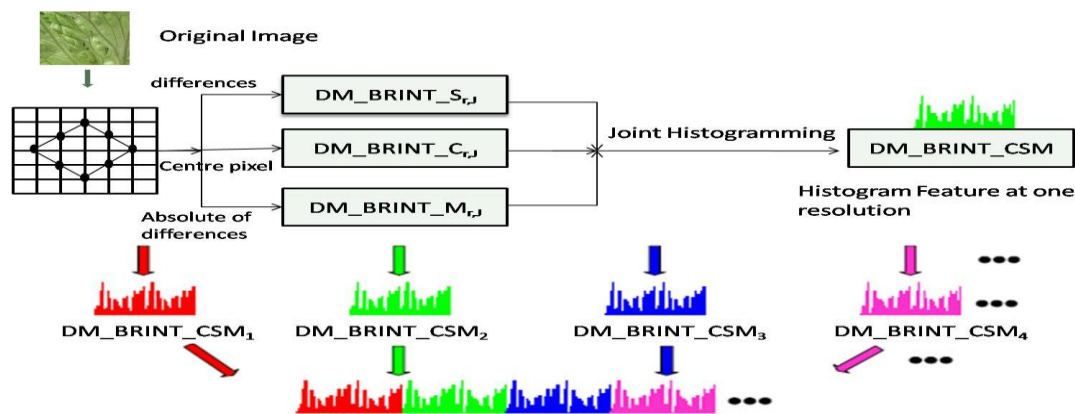


Fig. 3. The overall framework of the proposed descriptor

2.3.1 DM_BRINT_S Descriptor

Unlike BRINT_S diamond sampling structure is used to sample neighbor pixels around a central pixel k_c and consider only 8 pixels at the locations shown in Fig.2. The neighbors are $K_p=[K_0, K_1, \dots, K_7]^T$. Now compute LBP with respect to the center pixel:

$$DM_BNT_S = \sum_{i=0}^7 s(k_p - k_c) 2^i \quad (3)$$

Since 8 neighbors are used, a total of 256 patterns are possible and therefore feature length is 256. We use uniform rotation invariant patterns of DM_BNT_S to generate DM_BRINT_S thereby decreasing feature length and to extract relevant information. This step decreases the length of feature vector to 10.

2.3.2 DM_BRINT_M Descriptor

Similar to the above procedure, diamond sampling structure is used and then the magnitude of differences between central pixel k_c and 8 neighbor pixels is calculated:

$$d_p = |k_p - k_c|, \quad p = 0, 1, \dots, 7 \quad (4)$$

Then compute a binary pattern DM_BNT_M based on d_p as follows:

$$DM_BNT_M = \sum_{i=0}^7 s(d_p - n_r) 2^i \quad (5)$$

where n_r is the average of magnitude of differences (d_p). Similar to previous descriptor, uniform rotation invariant version of DM_BNT_M is used to get DM_BRINT_M.

2.3.3 DM_BRINT_C Descriptor

Similar to BRINT_C, compute a binary pattern by comparing central pixel with global mean of the image without boundary pixels.

$$DM_BRINT_C = s(k_c - \gamma) \quad (6)$$

Where γ is the global mean of the image without boundary pixels.

Now the joint histogram of DM_BRINT_S, DM_BRINT_M and DM_BRINT_C is the proposed descriptor. Now, name the descriptor as DM_BRINT_CSM or DM_BRINT. Thus far descriptor for single resolution only is created. For multi resolution analysis, different scales are needed to use.

2.4 Multi Resolution Approach

Thus far created descriptor for single resolution is devised. The number of pixels being averaged is changed to get descriptors for different resolutions. For instance, 2 pixels along radial direction of all neighbor pixels is averaged to get feature vectors for second resolution. Now Descriptors for 9 different resolutions are created and concatenated histograms of all resolutions to get the proposed texture descriptor DM_BRINT_CSM. The feature dimension of the proposed descriptor is $10 \times 10 \times 2 = 200$ for each resolution. Fig. 3 visualizes the full model of the proposed approach.

III EXPERIMENTAL RESULTS

The classification performance of the proposed approach is evaluated on two benchmark datasets which are available in public domain: OUTEX_TC_12_000 [5] and KTH-TIPS2b [8]. Extensive experiments are conducted on these two databases using either Nearest Neighbor Classifier (NNC) or non linear Support Vector Machine(SVM) classifier. In addition, γ^2 distance metric is used for NNC classifier. Exponential chi-square kernel is used for non linear SVM classifier as it has shown better performance in [9].

3.1 Experimental Setup

OUTEX_TC_12_000 is pictured under different lighting conditions and rotation changes and it is better suited for rotation invariance analysis. It consists of 24 classes of images with 200 samples per class imaged under nine rotation angles (0° , 5° , 10° , 15° , 30° , 45° , 60° , 75° and 90°). 20 samples from each class is used for training and remaining samples for testing. Each sample is of size 128×128 . The KTH-TIPS2b is imaged under different rotation changes, illumination conditions and scales. It consists of 432 images in each of the 11 different classes. 216 samples from each class is used for training and remaining samples for testing. KTH-TIP2b consists of texture samples which has 3 rotation angles, 4 different lightings and 9 different scales.

3.2 Methods in Comparison

The classification performance of the proposed approach is compared with below mentioned state-of-the-art methods:

- LTP: Uniform rotation invariant version of LTP is used by implementing for radius 3 and 24 neighbor pixels.

- CLBP_CSM: The 3 scale CLBP_CSM is implemented.
- BRINT: The recommended BRINT_CS_CM is implemented with sampling scheme of (1,8), (2,16), (3,24),..., (9,24).
- Mean LBP: Mean LBP which compares the central pixels with the average of neighbor pixels is implemented. 8 neighbor pixels are used to implement mean LBP.

To maintain uniformity, each texture sample is normalized to zero mean and unit standard deviation. Non linear SVM classification is done using LibSVM library. In the experiments opting for $C=2^{12}$ and $\gamma=2^{-5}$ produced best results.

3.3 Results

Table I compares the classification accuracy of the proposed descriptor with the state-of-the-art LBP variants on OUTEX_TC_12_000 database. In each table, the best result is highlighted in bold letters. This result indicates that the approach has shown better rotation invariance than other implemented methods.

TABLE I. Classification accuracies of the proposed approach in comparison to state-of-the-art results on OUTEX_TC_12_000 dataset using SVM classifier

Features	Classification Accuracies(%)
BRINT_CS_CM	98.13
CLBP_CS_CM_riu2	96.12
LTP	91.36
Mean LBP	86.78
Proposed method	99.62

TABLE II. Classification accuracies of the proposed approach in comparison to state-of-the-art results on KTH-TIPS2b dataset using NNC classifier

Features	Classification Accuracies(%)
BRINT_CS_CM	66.12
CLBP_CS_CM_riu2	65.44
LTP	62.12
Mean LBP	61.32
Proposed method	73.19

Table II compares the classification accuracies of the proposed approach with the implemented LBP variants. It shows that the proposed method is tolerant to rotation changes, scales and different lighting conditions.

TABLE III. Classification accuracies of the proposed approach in comparison to state-of-the-art results on KTH-TIPS2b dataset under the influence of gaussian noise at different levels of SNR using SVM classifier

Features	Classification Accuracies(%)				
	SNR=100	SNR=30	SNR=15	SNR=10	SNR=5
BRINT_CS_CM	66.11	58.32	49.65	44.90	32.17
CLBP_CS_CM_riu2	64.98	56.03	46.32	41.23	30.91
LTP	61.90	53.12	45.14	39.84	29.31
Mean LBP	61.01	50.86	43.21	36.15	29.51
Proposed method	73.13	59.36	50.85	43.07	35.12

TABLE IV. Classification accuracies of the proposed approach in comparison to state-of-the-art results on KTH-TIPS2b dataset under the influence of salt and pepper noise with zero mean and different variances using SVM classifier

Features	Classification Accuracies(%)				
	$\rho=0.05$	$\rho=0.1$	$\rho=0.2$	$\rho=0.3$	$\rho=0.4$
BRINT_CS_CM	65.87	60.30	56.10	53.91	46.87
CLBP_CS_CM_riu2	63.24	55.10	49.39	44.12	40.54
LTP	61.98	57.34	52.30	46.01	42.34
Mean LBP	60.96	53.10	50.06	45.06	41.76
Proposed method	72.68	67.76	61.21	56.56	49.30

As intended the noise robustness has been tested for the approach using three types of noises: Gaussian noise, salt and pepper noise and speckle noise. In Table III, the performance of DM_BRINT is compared on KTH-TIPS2b dataset affected with additive Gaussian noise at different levels of Signal to Noise Ratio. Table III shows that proposed method performs better in presence of Gaussian noise at different levels of Signal to Noise Ratio (SNR). In Table IV, the noise robustness analysis is performed using KTH-TIPS2b database corrupted

TABLE V. Classification accuracies of the proposed approach in comparison to state-of-the-art results on KTH-TIPS2b dataset under the influence of salt and pepper noise with zero mean and different variances using SVM classifier

Features	Classification Accuracies(%)				
	$\nu = 0.02$	$\nu = 0.05$	$\nu = 0.1$	$\nu = 0.2$	$\nu = 0.3$
BRINT_CS_CM	66.09	62.41	61.32	53.15	44.30
CLBP_CS_CM_riu2	65.44	61.31	60.07	51.32	42.01
LTP	63.54	60.10	59.34	49.81	40.90
Mean LBP	61.23	60.14	58.93	47.12	39.06
Proposed method	73.02	70.15	65.65	54.79	49.16

with salt and pepper noise under separate noise density ratios(ρ). Table IV proves that the proposed approach is more noise robust to salt and pepper noise than other LBP variants. Table V checks the performance against speckle noise for different LBP variants in place. Speckle noise of zero mean and different levels of variance is added. The proposed approach has shown significant improvement in the performance.

IV CONCLUSION

In this paper, we aimed to achieve the balance between low computation complexity, low feature dimensionality and noise robustness. These were accomplished by using effective diamond sampling structure to simplify the computations and noise robustness is achieved through averaging along radial direction. A new descriptor motivated by BRINT descriptor is created to achieve better classification accuracy and low feature dimensionality. We conducted experimental tests on two benchmark texture databases. Results showed that the proposed approach performs superior to other state-of-the-art LBP like methods both in noisy and noise free conditions. It denotes that the proposed approach is simple, robust to noise while having low feature dimension.

Acknowledgment

The first author gratefully acknowledges the contributions of Mr. K. Durga Ganga Rao for his suggestions and support to complete this work.

REFERENCES

- [1] L. Liu, Y. Long, P. Fieguth, S. Lao, G. Zhao, "BRINT: binary rotation invariant and noise tolerant texture classification." *IEEE Trans. Image Process.*, vol. 23, no.7, pp. 3071-3084, Jul. 2014.
- [2] T. Ojala, M. Pietikäinen, and T. Mäenpää, "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] M. Raja and V. Sadavisam, "Optimized local ternary patterns: A new texture model with set of optimal patterns for texture analysis," *J. Comput. Sci.*, vol. 9, no. 1, pp. 1–14, 2013.
- [4] 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, Jun. 2010.
- [5] T. Ojala, T. Mäenpää, M. Pietikäinen, J. Viertola, J. Kyllönen, and S. Huovinen, "Outex—New framework for empirical evaluation of texture analysis algorithms," in *Proc. 16th Int. Conf. Pattern Recognit.*, vol. 1, 2002, pp. 701–706.
- [6] M. Pietikäinen, T. Ojala, and Z. Xu, "Rotation-invariant texture classification using feature distributions," *Pattern Recognit.* vol. 33, no. 1, pp. 43–52, Jan. 2000.
- [7] C.-C. Chang and C.-J. Lin. (2001). *LIBSVM: A Library for Support Vector Machines* [Online]. Available: <http://www.csie.ntu.edu.tw/~cjlin/libsvm>
- [8] P. Mallikarjuna, M. Fritz, A. T. Targhi, E. Hayman, B. Caputo, and J.-O. Eklundh. (2006). *The KTH-TIPS and KTH-TIPS2 Databases* [Online]. available: <http://www.nada.kth.se/cvap/databases/kth-tips/>
- [9] B. Schölkopf and A. Smola, *Learning With Kernels: Support Vector Machines, Regularization, Optimization and Beyond*. Cambridge, MA, USA: MIT Press, 2002.
- [10] Zhibin Pan, Xiuquan Wu, Zhengyi Li, and Zhili Zhou, "Local Adaptive Binary Patterns Using Diamond Sampling Structure for Texture Classification", *IEEE Signal Processing Letters*, in press.
- [11] S. Liao, Max W. K. Law, and Albert C. S. Chung, "Dominant local binary patterns for texture classification," *IEEE Trans. Image Process.*, vol. 18, no. 5, pp. 1107–1118, May 2009.
- [12] Rakesh Mehta and Karen Egiazarian, "Texture classification using dense micro-block difference," *IEEE Trans. Image Process.*, vol. 25, no. 4, April 2016.