Texture Classification With High Order Local Pattern Descriptor: Local Derivative Pattern

Dr U S N Raju[1], A Sridhar Kumar[2], B Mahesh[3], Dr B Eswara Reddy[4]

GJCST Classification
I.2.10.I.3.7.1.4.7

***Abstract*-This paper proposes a novel method for texture classification using high-order local pattern descriptor: Local Derivative Pattern (LDP). LDP is used to encode directional pattern features based on local derivative variations. The nth order LDP is proposed to encode the (n-1)th order local derivative direction variations, which can capture more detailed information. The local texture information for a given pixel and its neighborhood is characterized by the texture units calculated in different ways, and the global textural aspect of an image is revealed by its texture spectrum. This paper uses the second, third and fourth order LDPs to classify the textures. For this classification, the texture images are taken from Brodatz album.**

Keywords- Local Derivative Pattern, Texture pectrum, Texture classification.

I. INTRODUCTION

Texture has long been an important topic in image processing [1,2,3,7,8,9,13,18]. Methods of texture analysis are usually divided into two major categories [8,15]. The first is the structural approach, where texture is considered as a repetition of some primitives, with a specific rule of placement. The traditional Fourier spectrum analysis and wavelet based analysis [11] are often used to determine the primitives and placement rule. Several authors have applied these methods to texture classification and texture characterization with a certain degree of success [5]. The second major approach in texture analysis is statistical method. Its aim is to characterize the stochastic properties of the spatial distribution of gray levels in an image. The gray tone co-occurrence matrix is frequently used for such characteristics. A set of textural features derived from the co-occurrence matrix is widely used to extract textural information from digital images [2,4].

Study of patterns on textures is recognized as an important step in characterization and classification of textures. Textures are classified recently by various pattern methods: preprocessed images [18], long linear patterns [10,17], and edge direction movements [6], Avoiding Complex Patterns [16], marble texture description [14]. Textures are also described and classified by using various wavelet transforms: one based on primitive patterns [19], and another based on statistical parameters [12].

[1]Professor, Dept. of CSE, Rajeev Gandhi Memorial College of Engg. & Technology, Nandyal, Kurnool (Dt.)-518 501, A.P., India, usnraju@gmail.com

[2]Senior Software Engineer, Inforaise Technologies Pvt. Ltd., Hyderabad, A.P., India, a.sridhar51@gmail.com

[3]Senior Software Engineer, Bangalore, Karnataka, India, mahesh544@gmail.com

[4]Associate Professor, Dept. of CSE, JNTU College of Engineering, Anantapur, A.P, India, eswarcsejntu@gmail.com

Recently, local descriptors have gained much attention in texture analysis for their robustness to illumination and pose variations. One of the local descriptors is local feature analysis (LFA) proposed by Penev et al. [25]. In LFA, a dense set of local-topological fields are developed to extract local features. Through discovering a description of one class objects with the derived local features, LFA is a purely second-order statistic method.

The recently proposed local binary pattern (LBP) features are originally designed for texture description [23,24,26]. The operator has been successfully applied to facial expression analysis [27], background modeling [22] and face recognition [21]. In face recognition, it achieves a much better performance than Eigenface, Bayesian and EBGM methods, providing a new way of investigating into the face representation. The idea behind using the LBP features is that a texture can be seen as a composition of micropatterns [21]. LBP in nature represents the first-order circular derivative pattern of images, a micropattern generated by the concatenation of the binary gradient directions. However, the first-order pattern fails to extract more detailed information contained in the input object. To the best of our knowledge, no high-order local pattern operator has been investigated for texture analysis. In fact, the high-order operator can capture more detailed discriminative information. A novel object descriptor, the high order Local Derivative Pattern (LDP) is proposed by Baochang Zhang et al [20]. LBP can conceptually considered as a non-directional first order local pattern, which is the binary result of the first order derivative image. The second order LDP can capture the change of derivative directions among local neighbors, and encode the turning point in a given direction.

The present paper computes the texture unit(TU) and texture spectrum by using second, third and fourth order LDPs in 00, 450, 900and 1350 on original texture images. Later a classification method has been introduced to classify and to find accuracy rate of classification. For this purpose the present paper is organized as follows. Methodology is defined in the second section while in the third section results and discussions are given. The last section deals with conclusions.

II. METHODOLOGY

Derived from a general definition of texture in a local neighborhood, LBP is defined as a grayscale invariant texture measure and is a useful tool to model texture images. The LBP operator labels the pixels of an image by thresholding the 3× 3 neighborhood of each pixel with the value of the central pixel and concatenating the results binomially to form a number. The thresholding function forthe basic LBP can be formally represented in Fig. 1(a) and it is represented in equation 1.

$$E_i = \begin{cases} 0 \ \ if \ \ V_i < V_0 \\ 1 \ \ if \ \ V_i \geq V_0 \end{cases} \quad for \quad i = 1,2,\ldots 8 \qquad ....(1)$$

where Ei, i=1,2…8 , is an 8-neighborhood point around E0 as shown in Fig. 1. Fig. 1(b) shows an example of obtaining an LBP. The resultant LBP for this is 101001111.

V_1	V_2	V_3
V_8	V_0	V_4
V_7	V_6	V_5

→

E_1	E_2	E_3
E_8		E_4
E_7	E_6	E_5

83	28	60
76	55	23
90	55	10

→

1	0	1
1		0
1	1	0

Fig. 1 (a)LBP representation(b)Example of obtaining the LBP

A. *Local Derivate Pattern (Ldp)*

Given an image $I(V)$, the first-order derivatives along 0^0, 45^0, 90^0 and 135^0 directions are denoted as $I'_\alpha(V)$where $\alpha=0^0$, 45^0, $90^0$and 135^0. Let V_0 be a point in $I(V)$, and V_i,i=1,…8 be the neighboring point around V_0 (see Fig. 1(a)). The four first-order derivatives at $V=V_0$are given in equations 2, 3, 4 and 5 for 0^0, 45^0, $90^0$and 135^0respectively[20].

$$I'_{0^0}(V_0) = I(V_0) - I(V_4) \qquad (2)$$

$$I'_{45^0}(V_0) = I(V_0) - I(V_3) \qquad (3)$$

$$I'_{90^0}(V_0) = I(V_0) - I(V_2) \qquad (4)$$

$$I'_{135^0}(V_0) = I(V_0) - I(V_1) \qquad (5)$$

The second-order directional LDP, $LDP_\alpha^2(V_0)$, in α direction at $V=V_0$ is defined as

$$LDP_\alpha^2(V_0) = \{ f(I'_\alpha(V_0), I'_\alpha(V_1)), f(I'_\alpha(V_0), I'_\alpha(V_2)), \ldots f(I'_\alpha(V_0), I'_\alpha(V_7)), f(I'_\alpha(V_0), I'_\alpha(V_8)) \} \qquad (6)$$

where f(.,.) is a binary coding function determining the types of local pattern transitions. It encodes the co- occurrence of two derivative directions at different neighboring pixels as

$$f(I'_\alpha(V_0), I'_\alpha(V_i)) = \begin{cases} 0 & if \quad I'_\alpha(V_i) . I'_\alpha(V_0) > 0 \\ 1 & if \quad I'_\alpha(V_i) . I'_\alpha(V_0) \leq 0 \end{cases} \quad i = 1,2,\ldots 8 \quad (7)$$

Finally, the second-order Local Derivative Pattern, $LDP^2(V)$, is defined as the concatenation of the four 8-bit directional LDPs as given in equation 8.

$$LDP^2(V) = \{ LDP_\alpha^2(V) \mid \alpha = 0^0, 45^0, 90^0, 135^0 \} \qquad (8)$$

To calculate the third-order Local Derivative Pattern, we first compute the second-order derivatives along 0^0, 45^0, 90^0 and 135^0 directions, denoted as $I''_\alpha(V)$ where $\alpha=0^0, 45^0, 90^0, 135^0$. The third-order Local Derivative Pattern, $LDP_\alpha^3(V_0)$, in α direction at $V=V_0$ is defined as

$$LDP_\alpha^3(V_0) = \{ f(I''_\alpha(V_0), I''_\alpha(V_1)), f(I''_\alpha(V_0), I''_\alpha(V_2)), \ldots f(I''_\alpha(V_0), I''_\alpha(V_7)), f(I''_\alpha(V_0), I''_\alpha(V_8)) \} \qquad (9)$$

where f(.,.) is difined as

$$f(I''_\alpha(V_0), I''_\alpha(V_i)) = \begin{cases} 0 & if \quad I''_\alpha(V_i) . I''_\alpha(V_0) > 0 \\ 1 & if \quad I''_\alpha(V_i) . I''_\alpha(V_0) \leq 0 \end{cases} \quad i = 1,2,\ldots 8 \quad (10)$$

$$LDP^3(V) = \{ LDP_\alpha^3(V) \mid \alpha = 0^0, 45^0, 90^0, 135^0 \} \qquad (11)$$

In a general formulation, the n^{th} order LDP is a binary string describing gradient trend changes in a local region of directional $(n-1)^{th}$ order derivative images $I'_\alpha(V)$as

$$LDP_\alpha^n(V_0) = \{ f(I_\alpha^{n-1}(V_0), I_\alpha^{n-1}(V_1)), f(I_\alpha^{n-1}(V_0), I_\alpha^{n-1}(V_2)), \ldots f(I_\alpha^{n-1}(V_0), I_\alpha^{n-1}(V_7)), f(I_\alpha^{n-1}(V_0), I_\alpha^{n-1}(V_8)) \} \qquad (12)$$

where $I_\alpha^{n-1}(V_0)$ is the $(n-1)^{th}$ order derivative in α direction at $V= V_0$. $f(I_\alpha^{n-1}(V_0), I_\alpha^{n-1}(V_i))$is defined in (11), which encodes the $(n-1)^{th}$ -order gradient transitions into binary patterns, providing an extra order pattern information on the local region.

$$f(I_\alpha^{n-1}(V_0), I_\alpha^{n-1}(V_i)) = \begin{cases} 0 & if \quad I_\alpha^{n-1}(V_i) . I_\alpha^{n-1}(V_0) > 0 \\ 1 & if \quad I_\alpha^{n-1}(V_i) . I_\alpha^{n-1}(V_0) \leq 0 \end{cases} \quad i = 1,2,\ldots 8 \quad (13)$$

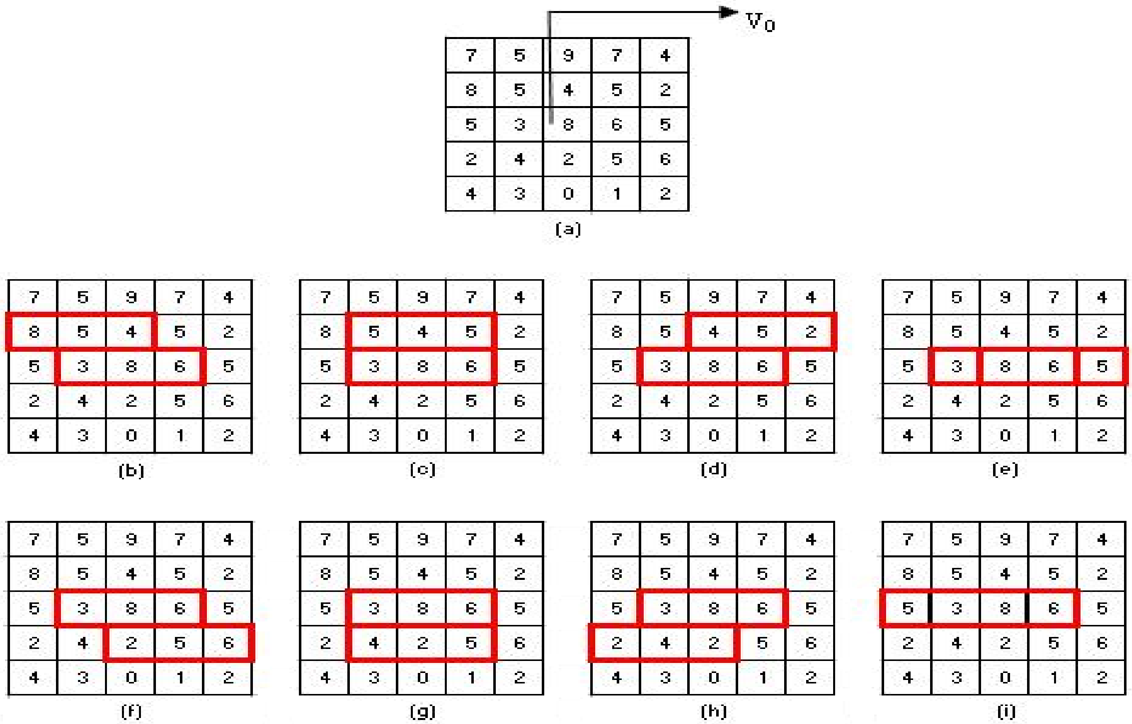

Fig. 2. Example to obtain the third order LDP(a) Original image (b) $f\left(I_0''(V_0), I_0''(V_1)\right)$ ***(c)*** $f\left(I_0''(V_0), I_0''(V_2)\right)$ ***(d)*** $f\left(I_0''(V_0), I_0''(V_3)\right)$ ***(e)*** $f\left(I_0''(V_0), I_0''(V_4)\right)$ ***(f)*** $f\left(I_0''(V_0), I_0''(V_5)\right)$ ***(g)*** $f\left(I_0''(V_0), I_0''(V_6)\right)$ ***(h)*** $f\left(I_0''(V_0), I_0''(V_7)\right)$ ***(i)*** $f\left(I_0''(V_0), I_0''(V_8)\right)$.

B. Algorithm For Evaluating Percentage Of Correct Classification On Images Using Local Derivative Pattern (LDP)

Begin

i. Take input Brodatz Textures Tk, k= 1 to 12.

ii. Subdivide the Tk , into 16 equal sized blocks. Name them as subimage TkSi, k=1 to 12 and i = 1 to 16.

iii. Select at random, a training sample sub image from each Tk, k= 1to 12 and denote it as TkSj where 'j' is any of the sample pieces 1 to 16 of a particular Tk.

iv. Calculate the LDP and Texture Spectrum for the second, third and fourth order LDPs by moving the 3×3 matrix across the sample with overlapping (Convolving), for TkSj.

v. To obtain Texture Spectrum value of testing subimage repeat step 3 for TkSm k= 1 to 12, m=1 to 16(m $\neq$ j).

vi. To classify a subimage TkSm, the distance between the training set and the testing samples is measured.

vii. The tested set falls into the Class k, k= 1 to 12, such that D (k) is minimum among all the D (k), k=1to 12.

viii. w for each texture Tk, k=1 to 12, we evaluate the percentage of correct classification (PCC) and list the output in the form of table.

$$PCC_k = \frac{Number\ of\ subimages\ correctly\ classified}{Number\ of\ subimages\ considered\ for\ testing} \times 100$$

End

III. RESULTS AND DISCUSSIONS

The Table 1 shows the percentage of correct classification (PCC) on 12 Brodatz textures [28] using original images derived from the second, third and fourth order LDPs respectively. The tables clearly indicate that for second order LDP the PCC is around 92% which has decreased to 83% for third order LDP and fourth order LDP. By using second order LDP except the textures D_1, D_4, D_5 and D_9 the remaining eight textures showing a PCC of 100%. But it is little bit different for third and fourth order LDPs. The PCC is also shown with the help of a graph in Fig. 3.

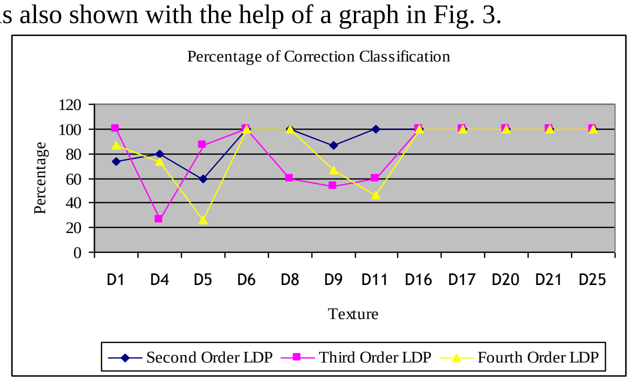

Fig. 3. Percentage of Correct Classification of Brodatz Textures

IV. CONCLUSIONS

This paper proposed a new method of texture classification using high order local patterns: Local Derivative Patterns (LDP). The second, third and fourth order LDP in the four directions i.e. 00, 450, 900 and 1350 are calculated from which texture spectrum is obtained. By using this texture spectrum the percentage of correct classification is obtained. The LDP extract high order local information by encoding various distinctive spatial relationships contained in a given local region. The experimental results clearly indicate that the percentage of correct classification for second order LDP is good when compared with third and fourth order LDP.

Table 1: Percentage of Correct Classification for the Brodatz Textures

Texture	Second Order LDP	Third Order LDP	Fourth Order LDP
D_1	73.33	100.00	86.67
D_4	80.00	26.67	73.33
D_5	60.00	86.67	26.67
D_6	100.00	100.00	100.00
D_8	100.00	60.00	100.00
D_9	86.67	53.33	66.67
D_{11}	100.00	60.00	46.67
D_{16}	100.00	100.00	100.00
D_{17}	100.00	100.00	100.00
D_{20}	100.00	100.00	100.00
D_{21}	100.00	100.00	100.00
D_{25}	100.00	100.00	100.00
Avg.	**91.67**	**82.22**	**83.33**

V. ACKNOWLEDGEMENTS

The authors would like to express their gratitude to Dr M. Santhi Ramudu, Chairman, and Mr. M Siva Ram, Managing Director Rajeev Gandhi Memorial College of Engineering and Technology for providing necessary infrastructure. Authors would like to thank Dr. Vakulabharanam Vijaya Kumar for his invaluable guidance which led to improvise the quality of this paper.

VI. REFERENCES

1) Bovik, A. C., Clark, M. and Geisler, W. S. Multichannel texture analysis using localized spatial filters, IEEE Trans. Patt. Anal. Mach. Intell., 12, 1, pp. 55-73, 1990.
2) Chang. T, and Kuo, C. C. J., Texture analysis and classification with tree-structured wavelet transform, IEEE Trans. Image Processing, 2, 4, pp. 429-442, 1993.
3) Chen, J. L. and Kundu, Unsupervised texture segmentation using multi-channel decomposition and hidden Markov models, IEEE Trans. Image. Processing, 4, 5, pp. 603-620, 1995.
4) Conners, R. W. Toward a set of statistical features which measure visually perceivable qualities of texture, in Proc. Pattern Recognition Image Processing Conf., pp. 382-390, 1979.
5) D'Astous, F. and Jernigan, M. E. Texture discrimination based on detailed measures of power spectmm, in Proc. IEEE Comput. Soc. Con5 on Pattern Recogn. and Image Process., pp. 83-86, 1984.
6) Eswara Reddy, B., Nagaraja Rao, A., Suresh, A. and Vijaya Kumar, V. Texture Classification by simple patterns on edge direction movements, IJCSNS, Vol.7 No.11, pp. 220-225, 2007.
7) Haralick, R. M. et al., Texture features for image classification, IEEE Trans. Syst. Man Cybern. SMC-3, 6, pp. 610-621, 1973.
8) Haralick, R. M. Statistical and structural approaches to texture, Proc. of 4th Int. Joint Conf. Pattern Recognition, pp. 45-60, 1979.
9) He, D. C. and Wang, L. Textural filters based on the texture spectrum, Patt. Recogn. 24, 12, pp.1187-1195, 1991.
10) Krishna, V. V., Vijaya Kumar, V ., Raju, U.S.N., Saritha, B. Classification of textures based on distance function of linear patterns using mathematical morphology, Proceedings of ICEM, conducted by JNT University, India, 2005.
11) Mallat, S. Multi frequency Channel Decomposition of Images and Wavelet Models, IEEE Trans. Acoustic, Speech and Signal Processing, 37, 12, pp. 2091-2110, 1989.
12) Raju, U.S.N., Vijaya Kumar, V. , Suresh, A. and Radhika Mani, M. Texture Description using Different Wavelet Transforms Based on Statistical Parameters,proceedings of the 2nd WSEAS International Symposium on WAVELETS THEORY & APPLICATIONS in Applied Mathematics, Signal Processing & Modern Science (WAV '08), Istanbul, Turkey, pp. 174-178, 2008.
13) Salari, E. and Ling, Z. Texture segmentation using hierarchical wavelet decomposition, Patt. Recogn. 28, 12, pp.1819-1824, 1995.
14) Suresh, A., Raju, U.S.N., Nagaraja Rao, A. and Vijaya Kumar, V., An Innovative Technique of Marble Texture Description Based on Grain Components,International Journal of Computer Science and Network Security, Vol.8 No.2, pp. 122-126, 2008.
15) Van Gool, L., Dewaele, P. and Oosterlinck, A. Survey-texture analysis anno 1983, Computer Vision, Graphics Image Processing, Vol. 29, PP. 336-357, 1985.
16) Vijaya Kumar, V. , Eswara Reddy, B., Raju, U.S.N. and Suresh, A. Classification of Textures

by Avoiding Complex Patterns, Science publications, Journal of Computer Science , 2008.

17) Vijaya Kumar, V., Eswara Reddy, B. ,Raju, U.S.N. and Chandra Sekharan, K. An Innovative Technique of Texture Classification and Comparison Based on Long Linear Patterns, Journal of Computer Science 3 (8): pp.633-638, 2007.
18) Vijaya Kumar, V., Eswara Reddy, B. and Raju, U.S.N. A measure of patterns trends on various types of preprocessed images, IJCSNS, Vol.7 No.8, pp. 253-257, 2007.
19) Vijaya Kumar, V., Raju, U.S.N. , Chandra Sekaran, K. and Krishna, V. V. A New Method of Texture Classification using various Wavelet Transforms based on Primitive Patterns, ICGST International Journal on Graphics, Vision and Image Processing, GVIP, Vol.8, Issue 2, pp. 21-27, 2008.
20) Baochang Zhang, Yongsheng Gao, et. Al. "Local Derivative Pattern Versus Local Binary Pattern: Face Recognition with High-order Local Pattern Descriptor" IEEE Trans. On Image Processing, Vol. 19, No.2, 2010.
21) Ahonen T., Hadid A., and Pietikainen M., "Face description with local binary patterns: Application to face recognition," IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 12, pp. 2037-2041, 2006.
22) Heikkila M. and Pietikainen M., "A texture-based method for modeling the background and detecting moving objects," IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 4, pp. 657-662, 2006.
23) Ojala T., Pietikainen M., and Harwood D., "A comparative study of texture measures with classification based on feature distributions," Pattern Recognit., vol. 29, no. 1, pp. 51-59, 1996.
24) Ojala T., Pietikainen M., and Maenpaa T., "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, 2002.
25) Penev P. S. and Atick J. J., "Local feature analysis: A general statistical theory for object representation," Network: Comput. Neural Syst., vol. 7, no. 3, pp. 477-500, 1996.
26) Pietikaainen M., Ojala T., and Z. Xu, "Rotation-invariant texture classification using feature distributions," Pattern Recognit., vol. 33, no. 1, pp. 43-52, 2000.
27) Zhao G. and Pietikaainen M., "Dynamic texture recognition using local binary patterns with an application to facial expressions," IEEE Trans. Pattern Anal. Mach. Intell., vol. 29, no. 6, pp. 915–928, Jun. 2007.
28) Brodatz, P. Textures A Photographic for Artists and Designers, Dover, NY, 1966.