Segmentation Method based on Texture Unit Approach Derived on Local Directional Pattern (LDP)

K. Venkata Subbaiah
Research Scholar, Rayalaseema University, Kurnool, AP, India
Assoc. Prof. in Dept. of CSE, PBR Visvodaya Institute of Technology & Science, Kavali, A.P., India

V. Vijaya Kumar
Professor, Dean and Director for CACR, Anurag Group of Institutions (Autonomous), Hyderabad, Telangana, India

ABSTRACT
Image segmentation is one of the crucial steps for image analysis, interpretation and recognition. This paper presents cross diagonal neighborhood approach based on local direction pattern (LDP) descriptor. Edge based segmentation divides images into regions based on local edge responses. The local attributes and edge responses are the crucial factors for edge based segmentation scheme. The LDP descriptor precisely measures the amount of each edge response in and around a centre pixel. The LDP overcomes the noise related problems of the local binary operator (LBP). On LDP images three categories of texture units are derived by partitioning the 3 x 3 neighborhood in to cross texture unit (CTU) and diagonal texture unit (DTU), to reduce the huge dimensionalities involved in the basic texture units and to characterize the local edge information precisely. The segmentation method is tested on five large databases namely Wang, Oxford flowers, Indian facial expressions, Brodatz textures and standard images from Google. The segmentation results demonstrate the efficacy of the proposed method.

Keywords
LDP, Texture unit; cross and diagonal; edge responses;

1. INTRODUCTION
Segmentation of an image is a difficult problem because it is difficult to predict and know *a priori*, what types of textures exist in an image, what regions have which textures and how many textures there are. Segmentation methods can be classified in to supervised or unsupervised. Unsupervised segmentation is one of the exigent segmentation because no *priori* information about the image textures is available. That’s why it has only limited success so far. Early methods of unsupervised segmentation are developed based on various methods like pyramid node linking [1], split-and-merge methods [2], a quadtree method [3] and selective feature smoothing with clustering [4]. Later the segmentation methods based on feature smoothing [5], local linear transforms [6], Markov random field models [7], autoregressive models [8], fractal dimension [9], multichannel filtering [10], wavelets [11], hidden Markov models [12], Markov random fields for color textures [13] are proposed in the literature. These methods achieved good results for a minute set of fine-grained texture like mosaics; however they need to have prior knowledge of the image contents like number of textures and regions. And some segmentation methods typically performed poor results for natural images containing non uniform textures.

The segmentation methods are also broadly divided into three categories: edge-based [14, 15], region-based [16] and pixel-based segmentation [17]. Region-based segmentation can identify partitions in a given image. The most popular region based methods are graph-based segmentation [18] and mean shift (MS) based segmentation [19, 20, 21] methods. The segmentation methods based on normalized cuts are also proposed [22- 27] and among these, the multi-scale normalized cut approach [26] greatly improves the performance. The histogram based segmentation [28-32] methods represent pixel based segmentation approaches.

One of the extremely difficult and challenging tasks of segmentation is to discriminate small regions, from large and global texture primitives. One of the most crucial factors for successful texture segmentation is how to choose highly discriminating local texture features. And this aspect was neglected in earlier approaches. The local features also depend upon the size of the window. Local Binary Pattern (LBP) proposed by ojala et al. [33] is a popular tool used to capture local primitives of an image texture precisely. Good texture discrimination can be obtained with LBP. The LBP or gray-scale difference operator with statistical measures shown higher performance rates than the existing methods [34, 35, 36]. The only problem with LBP is a small noise may predict local primitives differently. The reason for this is the threshold in LBP is based on the intensity levels around centre pixel of the window. To overcome this local direction pattern (LDP) is proposed in this paper. This paper presents an efficient hybrid method for unsupervised texture segmentation based on local texture description using LDP, followed by the derivation of cross and diagonal texture unit.

The present paper organized as follows: The section 2 describes the related work. The section 3 and 4 demonstrates the proposed method and results with discussions respectively. The section 5 describes the conclusion.

2. RELATED WORK
2.1 Local Binary Pattern (LBP)
A texture is not only characterized by the gray level value of a pixel it is mainly influenced by the local information of the pixel surroundings. The Local Binary Pattern (LBP) was derived by Ojala et al. [33]. The LBP extracts the local information precisely. LBP is widely studied recently in age classification [37- 40], face recognition [41, 42], texture classification [43], segmentation [44, 45], image retrieval [46, 47, 48] etc. and it obtained a good results.

The neighboring pixels of a 3 x 3 window are denoted in the present paper as $\{n_c, n_0, n_1 \dots n_7\}$, where $n_c$and$n_0, n_1 \dots n_7$ represents the intensity values of the central and neighboring pixel and $n_i (0 \le i \le 7)$. The LBP initially derives binary patterns for the neighborhood pixels based on a threshold as given in equation 1.

$$b_i = \begin{cases} 0 & \Delta p_i \ge 0 \\ 1 & \Delta p_i < 0 \end{cases} \qquad (1)$$

where $\Delta p_i = n_i - n_c$, and i= 0 to 7

The binary elements of the neighborhood pixels are multiplied by corresponding binary weights and concatenated to form the unique LBP code as given in equation 2.

$$LBP_{P,R} = \sum_{i=0}^{i=7} b_i \times 2^i \quad (2)$$

This LBP code replaces the central pixel. By repeating this on entire image in overlapped manner the image is converted in to a LBP coded image. Thus a single LBP code represents local micro texture information around a pixel by a single integer code LBP.

2.2 Local Derivational Pattern (LDP)

LBP suffers with noise and a small noise may change LBP code drastically to a minimum to a maximum. Further LBP is not capable of representing edge responses. To address the above and to capture local texture information the present paper utilized the LDP instead of LBP. A small fluctuation may lead to abnormal variation of LBP code as shown in Fig.1 and Fig.2.

141	140	141
145	142	140
141	141	142

(a) Actual LBP image

→

0	0	0
1		0
0	0	1

(b) Generation of binary patterns based on equation 1

→

2^0	2^1	2^2
2^7		2^3
2^6	2^5	2^4

(c) Corresponding Weights

→

144

(d) LBP Code

Fig.1: LBP code generation for a non-noisy window.

143	140	143
145	142	140
143	143	142

(a) LBP window with error

→

1	0	1
1		0
1	1	1

(b) : Generation of binary patterns based on equation 1

→

2^0	2^1	2^2
2^7		2^3
2^6	2^5	2^4

(c):Corresponding Weights

→

245

(d) LBP Code

Fig. 2: LBP code generation for a noisy window of Fig.1.

In Fig. 2(a) small noise changed the gray level value of the neighboring pixels from 141 to 143 and this has changed the LBP code drastically from 144 to 245.To address this problem local directional pattern (LDP) [49] is introduced in the literature. The present research computes edge response values in eight directions of a particular pixel based on Kirsch masks in eight different orientations (M_0~M_7). These masks are shown in the Fig.3. Eight edge response values will be obtained (m_0, $m_1 \ldots m_7$) from these m_0 to m_7. And they represent significant edges in these directions. The k-most significant or top edge response values (m_i/(i=0,1…7) are selected for formation of LDP and corresponding directional bits are assigned to 1. The (8-k) remaining directional bits are set to 0. The reason for this is the presence of corner or edge indicates a high edge response value in a particular direction. Using this, LDP code is derived by equation 3.

$$LDP\,(x_c, y_c) = \sum_{i=0}^{7} m_i * 2^i \quad (3)$$

The proposed method take the three greatest responses, i.e. k=3. The LDP code generation on a 3x3 neighborhood is shown in Fig.4.

-3	-3	5
-3	0	5
-3	-3	5

M_0

-3	5	5
-3	0	5
-3	-3	-3

M_1

5	5	5
-3	0	-3
-3	-3	-3

M_2

5	5	-3
5	0	-3
-3	-3	-3

M_3

5	-3	-3
5	0	-3
5	-3	-3

M_4

-3	-3	-3
5	0	-3
5	5	-3

M_5

-3	-3	-3
-3	0	-3
5	5	5

M_6

-3	-3	-3
-3	0	5
-3	5	5

M_7

Fig.3: Kirsch edge response masks in eight directions used in LDP.

32	65	48
69	46	18
94	68	16

Mask index	m_7	m_6	m_5	m_4	m_3	m_2	m_1	m_0
Mask value	-414	194	618	330	98	-70	-182	-574
Rank	7	3	1	2	4	5	6	8
Binary patterns for k=2	0	0	1	1	0	0	0	0
Binary patterns for k=3	0	1	1	1	0	0	0	0
LDP code For k=2	48							
LDP code For k=3	112							

Fig.4: Transformation of LDP code for K=2 and K=3.

78	73	82	
73	72	27	LBP=11000111
89	42	52	LDP= 00011100

(a)

78	73	82	
71	72	27	LBP= 01000111
89	42	52	LDP= 00011100

(b)

Fig.5: Stability of LDP Vs. LBP (a) 3x3 image neighborhood (b) Image neighborhood with noise.

The LDP code produces more stable pattern over the LBP in the presence of noise, illumination differences and various conversion schemes of color textures into gray textures. The Fig.5 shows an image neighborhood. The LBP code 199 is derived on this based on a threshold i.e. the gray level value of the centre pixel. The derived LBP code is a uniform LBP (ULBP) and treated as one of the fundamental texture units. The LDP code with k=3 derives a value 28 for Fig. 5 (a). The Fig.5 (b) represents the corrupted window of the Fig.5 (a), with a small fluctuation. The LBP code becomes 71. And it is a non-uniform LBP and will be treated as miscellaneous in LBP applications. There is no change in LDP code by this fluctuation. This is because gradients are more stable than gray level values under and non-monotonic illumination changes.

32	65	48	0	1	1		
69	49	18	1		0		226
94	68	16	1	1	0		

Fig.6: LBP code for the noisy window of Fig.4.

The LDP code derived from Fig.4 for k=3 is 112. The LBP code for Fig.4 is 230 and it is a ULBP window. If a small random noise changes the centre pixel value of Fig.4 from 46 to 49, the LDP value remains the same as 112. However the LBP value fluctuates from 230 to 226 and this is shown ion Fig.6.The LDP code is not at all influenced by the random noise in this case, mainly because the LDP is not dependent on the gray level value of centre pixel. LBP is always derived based on the gray level value of centre pixel and that's why LBP code changed drastically.

2.3 Basic Texture Unit

The TU was introduced and described in detail by D.C. He and Li Wang [50].The TU characterizes the local texture information of a centre pixel on a 3 x 3 neighborhood. The TU is derived using two steps. In step one the 3 x 3 neighborhood pixel values are quantized in to ternary values and they are called as "texture unit elements (TUE)" and denoted as T_i as shown in equation 4.

$$T_i = \begin{cases} 0 \ if \ n_i < n_c \\ 1 \ if \ n_i == n_c \quad for \ i = 0,1,2,\dots 7 \\ 2 \ if \ n_i > n_c \end{cases} \quad (4)$$

In step two the texture unit number (TU_n) is derived by multiplying the TUE with the corresponding weights (powers of base 3) and summation of these corresponding weights results the texture unit number (TU_n) as shown in equation 5.

$$TU_n = \sum_{i=0}^{7} T_i * \ 3^i, T_i \epsilon \{0,1,2\} \ and \ TU_n \ \epsilon \{0,1,2,\dots 3^{8-1}\} \quad (5)$$

The TU_n can have a value ranging from 3^0 to 3^8 -1 i.e. 0 to 6561. One of the disadvantage of this representation is even a small noise may fluctuate the TU_n drastically. The process of TU_n evaluation is given in Fig.7.

170	53	140	2	0	0	3^0	3^1	3^2	
153	155	20	0		0	3^7		3^3	2
70	60	100	0	0	0	3^6	3^5	3^4	

(a) Before noise.

170	55	140	2	0	0	3^0	3^1	3^2	
155	155	20	1		0	3^7		3^3	2189
70	60	100	0	0	0	3^6	3^5	3^4	

(b) After noise.

Fig.7: The 3 x 3 window before and after noise.

In the above window a small fluctuation of noise converted one or more neighboring pixels (shown in red) values from 153 to 155 (Fig.7) and this has drastically changed the TU_n. The TU_n before and after noise are 2 and 2189 respectively. To overcome this, the present paper used a threshold value in deriving the ternary.

3. PROPOSED LDP BASED CROSS AND DIAGONAL TEXTURE UNIT (LDP-CD-TU) SEGMENTATION APPROACH

The present method initially identifies the fundamental local regions by using the LDP concept as given in section 2 and on LDP coded image the binary, ternary and quinary texture unit elements and numbers TUn are derived using a threshold. Initially the given image is transformed into a "LDP" coded image. The "Texture Unit Elements (TUE)" are derived using a threshold on each 3 x 3 window of LDP coded image. The present paper derived three types of TUE values on each 3 x 3 window based on a threshold 'k'. The first category of TUEs (binary) consists of two values {0,1} and the second and third category of TUEs consists of ternary

{0,1,2} and Quinary values {0,1,2,3,4}. The binary TUE is derived using a threshold similar to LBP. The ternary TUE values are derived based on a threshold k as given in equation 6. .

$$.T_i = \begin{cases} 0 \ if \ n_i < n_c - k \\ 1 \ if \ n_i \geq n_c - k \ and \ n_i < n_c + k \\ 2 \ if \ n_i \geq n_c + k \end{cases} \quad (6)$$

The Ternary TU (TTUn) number is computed in Base-3 as given in equation (7).

$$TTU_n = \sum_{i=0}^{7} T_i \, 3^{(i)}. \ T_i \in \{0,1,2\} \text{ and } TTU_n \in \{0,1,2,\dots\dots 6561\} \quad (7)$$

The advantage of the proposed TTU_n is it overcomes the small fluctuation of noise problems easily (Fig.1). The TTU_n, before and after noise for the Fig.7 is 2189 and 2189 only by using a small threshold of 2. The range of TTU_n in this case is same as without threshold i.e. 3^0 to 3^8 -1 i.e. 0 to 6561.

One of the main disadvantage of the above ternary valued texture element approach is it fails in dealing accurately with the regions of natural images even in the occurrence of small noise fluctuations and the dissimilar processes of caption and digitization. The human eye perceives two or more neighboring pixels as equal even though they differ with a small value. In such situations the TU of homogeneous images appears with more number of ones to the human eye because it can perceive ones. That is mostly for the human eye the texture unit elements will have only two values either {0 , 1 } or { 0, 2} which means that the real number of possible textures is 2^8, i.e., 256 out of 6561, and the texture units will never be totally covered, which misuses the power of TU method. To address this present research derived a quinary (five) valued {0, 1, 2, 3 and 4} texture unit elements based on threshold 'k' as given in equation 8 .

$$Q_i = \begin{cases} 0 & \text{if} \quad n_i < n_c \quad \text{and} \quad n_i < n_c - k \\ 1 & \text{if} \quad n_i < n_c \quad \text{and} \quad n_i \geq n_c - k \\ 2 & \text{if} \quad n_i = n_c \\ 3 & \text{if} \quad n_i > n_c \quad \text{and} \quad n_i <= n_c + k \\ 4 & \text{if} \quad n_i > n_c \quad \text{and} \quad n_i > n_c + k \end{cases} \quad \text{for } i = 0,1,2,3,\ldots,7 \qquad (8)$$

The "Quinary TU" (QTU) number (QTU_n) is computed in base-5 as given in equation 9. The QTU_n will have a range of values from 0 to 2020, thus the computation time is very less when compared to basic approach..

$$QTU_n = \sum_{i=0}^{7} Q_i \cdot 5^{(i)/2}. \; Q_i \in \{0,1,2,3,4\} \; and \; QTU_n \in \{0,1,2,\ldots\ldots 2020\} \qquad (9)$$

For example, the process of evaluating QTU_n from a sub image of 3×3 using a threshold 2 is shown in Fig. 8.

90	130	145
160	140	200
100	140	250

→

0	1	3
4		4
0	2	4

QTU_n= 1292

(a) **(b)** **(c)**

Fig. 8: (a) Original sub image (b) Representation of fuzzy texture elements (c) Derived QTU_n.

The present segmentation approach partitioned the TUE of a 3x 3neighborhood in to two groups namely Cross Texture Unit Elements (CTUE) and Diagonal Texture Unit Elements (DTUE). From this the paper computed Cross Texture Unit (CTU) and Diagonal Texture Unit (DTU) to overcome the dimensionality problem of BTU, TTU and QTU, where the range of TU are 0 to 255, 0 to 3561 and 0 to 2020. The dimensions of the proposed three types of Cross and Diagonal TU (CDTU) are demonstrated in Table 1.

Existing TU			Proposed CDTU		
Binary TU	Ternary TU	Quinary TU	Binary CDTU (BCDTU)	Ternary CDTU (TDTU)	Quinary CDTU (QCDTU)
256	6562	2021	2x 16	2x 81	2 x 624

Table 1: Dimensions of the existing and proposed Cross and Diagonal TU (CDTU).

To derive significant edge, corner and other information this paper used the OR operation in between CTU and DTU to derive LDP based CDTU image as shown in Fig. 9.

n_0	n_1	n_2
n_3	n_c	n_4
n_5	n_6	n_7

T_0	T_1	T_2
T_3	T_c	T_4
T_5	T_6	T_7
T_0	T_1	T_2

T_0*5^0	$T_1*5^{1/2}$	$T_2*5^{2/2}$
T_3*5^0	$T_c*5^{1/2}$	$T_4*5^{2/2}$
T_5*5^0	$T_6*5^{1/2}$	$T_7*5^{2/2}$

T_0*5^0	T_1*5^0	T_2*5^0
$T_3*5^{1/2}$	$T_c*5^{1/2}$	$T_4*5^{1/2}$
$T_5*5^{2/2}$	$T_6*5^{2/2}$	$T_7*5^{2/2}$

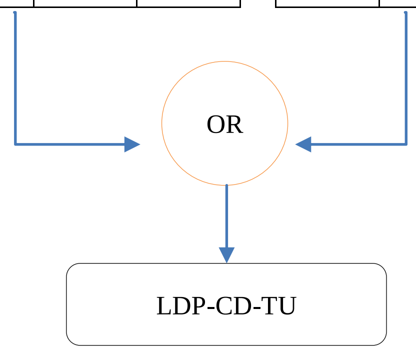

Fig.9: Formation of LDP-CD-TU

4. RESULTS AND DISCUSSION

The proposed LDP-CD-TU segmentation method is tested on five large databases namely Wang [51], Oxford flowers [52], Indian facial expressions [53] and Brodatz textures [54] . We have tested the LDP-CD-TU segmentation method on 200 images from each of the above data bases and this result to a total of 5 x 200= 1000 different images. The database images are in both color and gray level. The color images are converted in to gray level images using HSV color space. The HSV model is more natural and it is approximately and perceptually uniform than other color models like RGB and CIE. The HSV color model does not introduce false colors (hues).

The proposed LDP-CD-TU segmentation scheme is implemented with 3 categories on the above datasets i.e. category 1: Binary-micro texture unit (LDP-CD-BTU), category-2: LDP-CD-TTU and category 3: LDP-CD-TU. The proposed 3 categories of the segmentation scheme is displayed (10 images) step wise in Fig. 10, Fig.11, Fig.12 and Fig. 13.

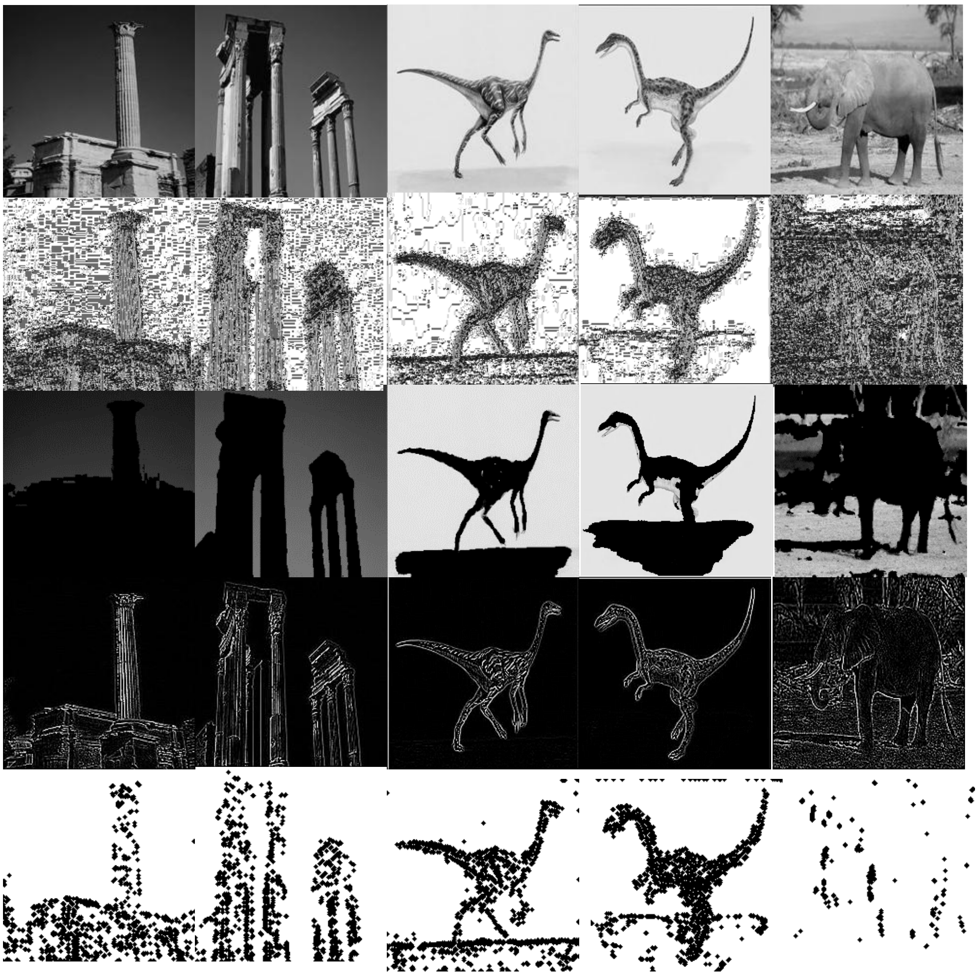

Fig.10: Segmentation results of proposed methods on Wang dataset: Row-1: Original images; Row-2: Results of LDP; Row-3: Results of LDP-CD-BTU ; Row-4: LDP-CD-TTU ; Row-5: LDP-CD-QTU.

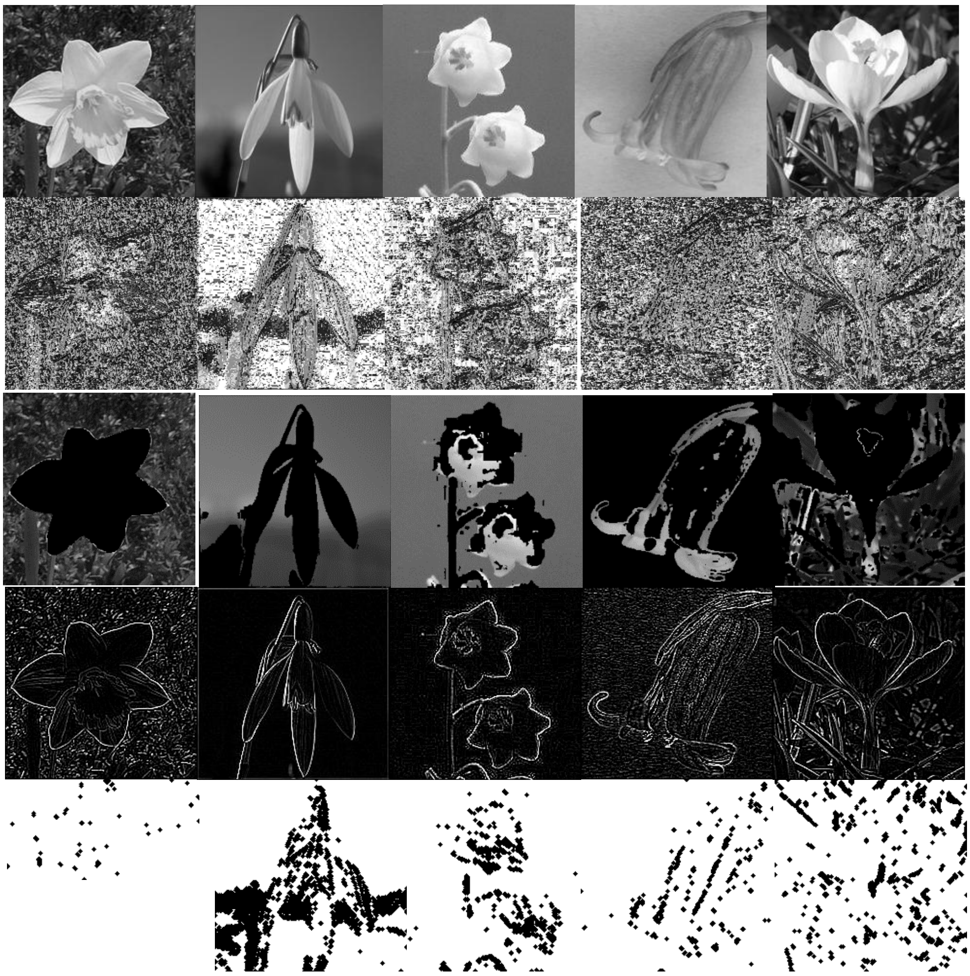

Fig.11: Segmentation results of proposed methods on Oxford flowers dataset: Row-1: Original images; Row-2: Results of LDP; Row-3: Results of LDP-CD-BTU ; Row-4: LDP-CD-TTU ; Row-5: LDP-CD-QTU.

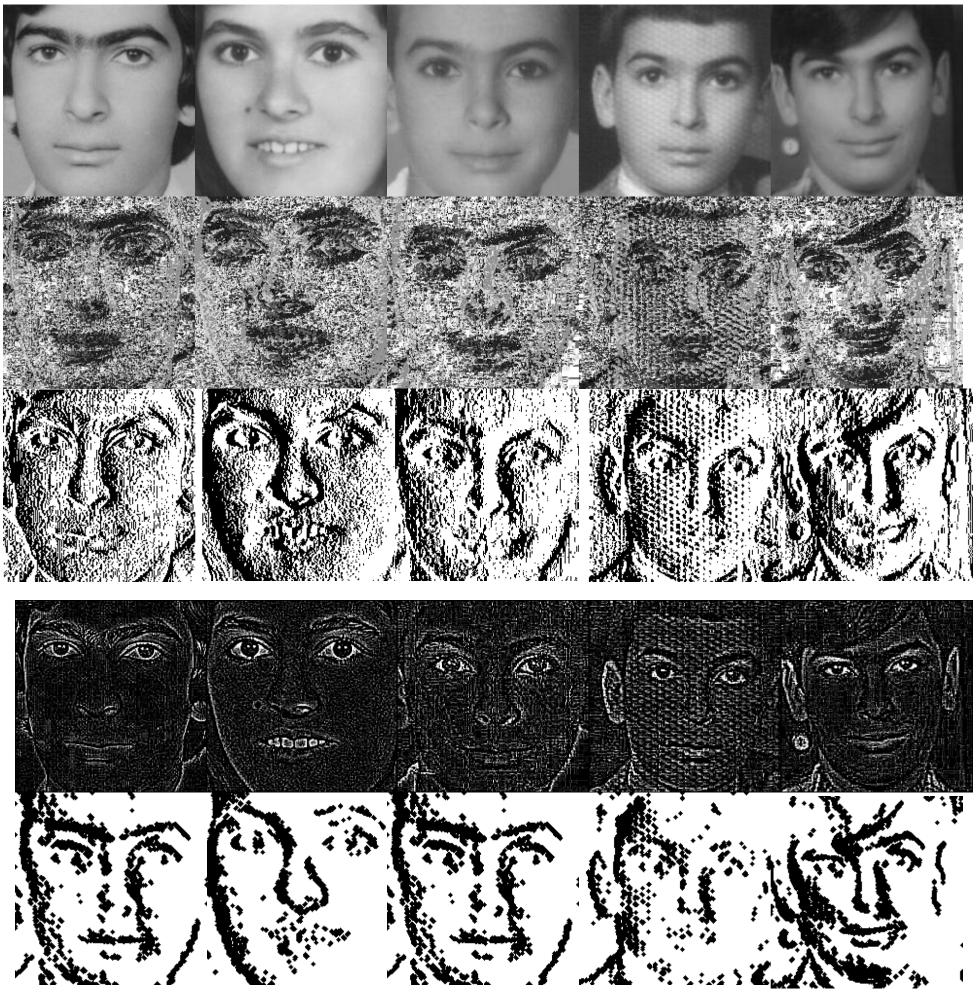

Fig.12: Segmentation results of proposed methods on Indian facial image dataset: Row-1: Original images; Row-2: Results of LDP; Row-3: Results of LDP-CD-BTU ; Row-4: LDP-CD-TTU ; Row-5: LDP-CD-QTU.

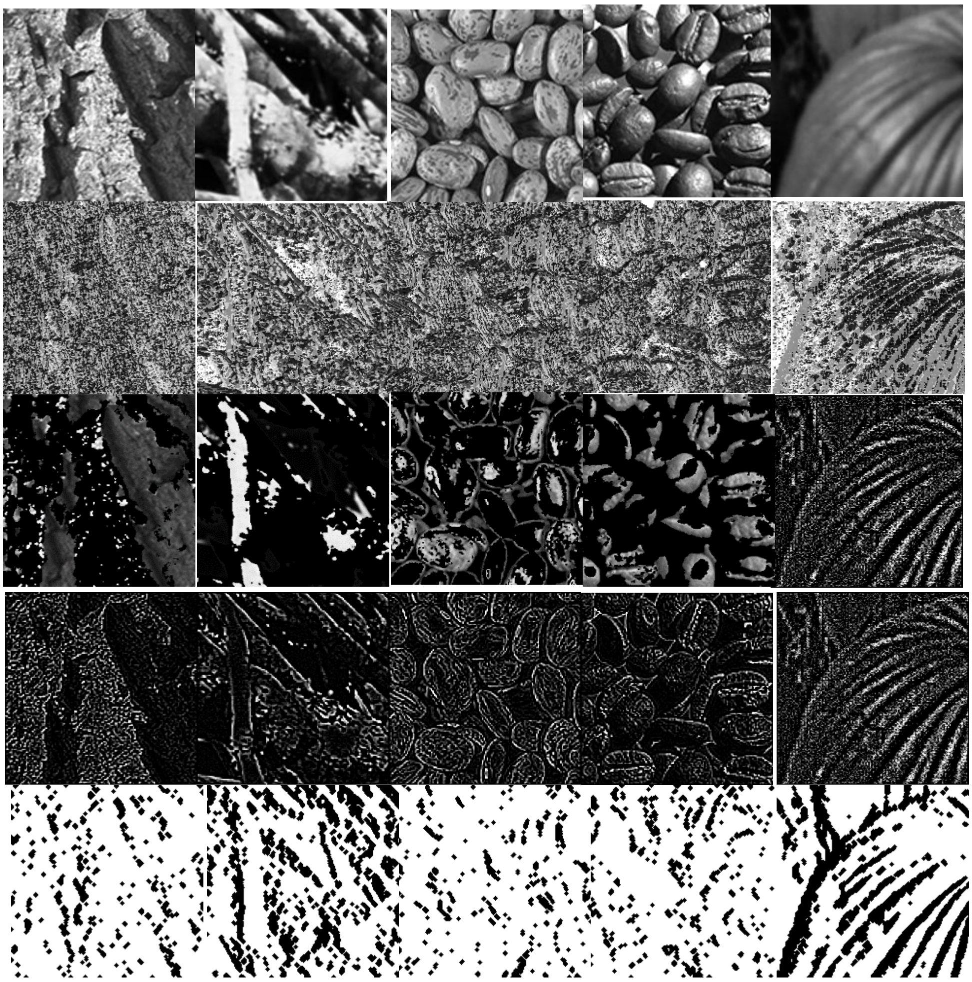

Fig.13: Segmentation results of proposed methods on Brodtaz textures dataset: Row-1: Original images; Row-2: Results of LDP; Row-3: Results of LDP-CD-BTU; Row-4: LDP-CD-TTU ; Row-5: LDP-CD-QTU.

The LDP-CD-BTU segmentation scheme (without threshold) yielded poor results for the facial images and completely failed in tracing the objects. This is due to the poor quantization of the gray level images without any threshold. The LDP-CD-TTU segmentation scheme yielded better results than LDP-CD-BTU. 80% all facial images with different orientations, background and expressions have shown good borders. The LDP-CD-QTU clearly exhibited a good segmentation than other two proposed methods. This is because the proposed LDP-CD-QTU approach accurately deals with the small noise, fluctuations and dissimilar processes of caption and digitization that present in natural images and textures.

The present research evaluated the segmentation metrics discrepancy, entropy, standard deviation and internal region contrast for the proposed LDP-CD-BTU, LDP-CD-TTU, LDP-CD-QTU and other existing methods [101, 134] and results are plotted in graphs Fig. 14 to Fig. 17. The proposed LDP-CD-QTU shows high discrepancy (Fig.14), entropy value in between 1 to 1.3 (Fig. 15) and lower standard deviation (Fig.16) indicates a good segmentation than the other existing methods. The proposed LDP-CD-QTU exhibits low internal region contrast, which indicates (Fig.17) a high uniformity within the regions.

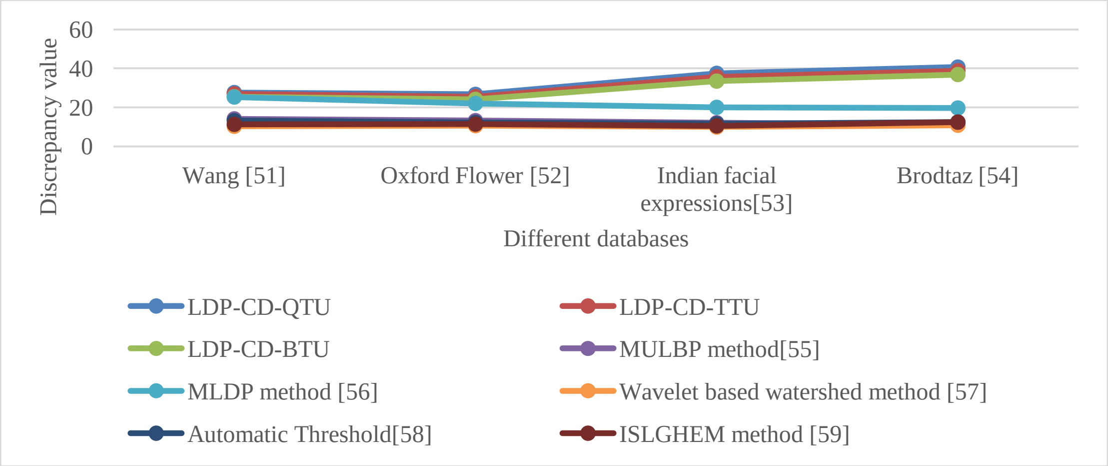

Fig. 14: Discrepancy graph of considered segmentation methods.

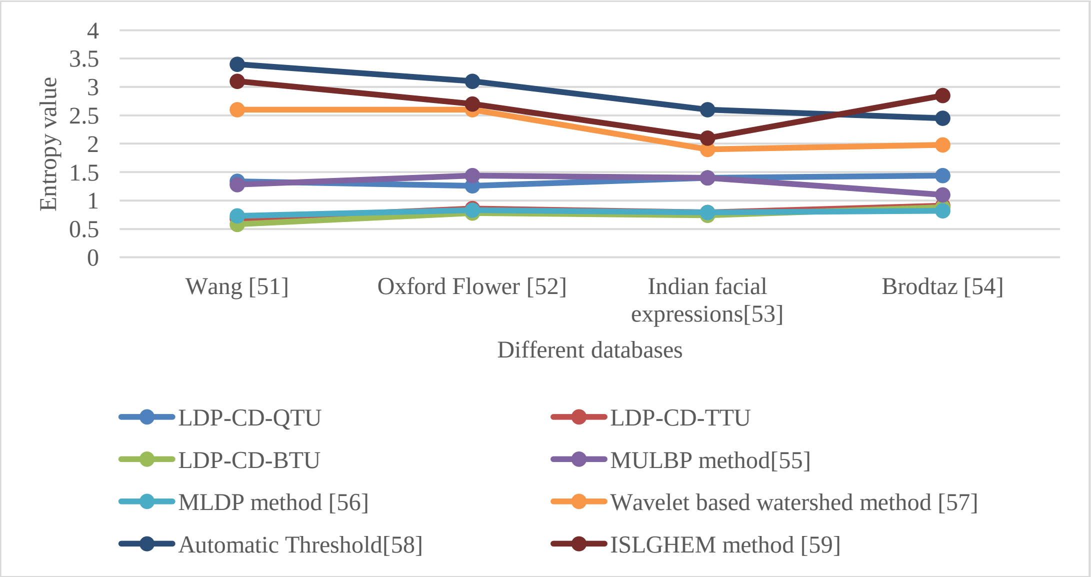

Fig. 15: Entropy graph of considered segmentation methods

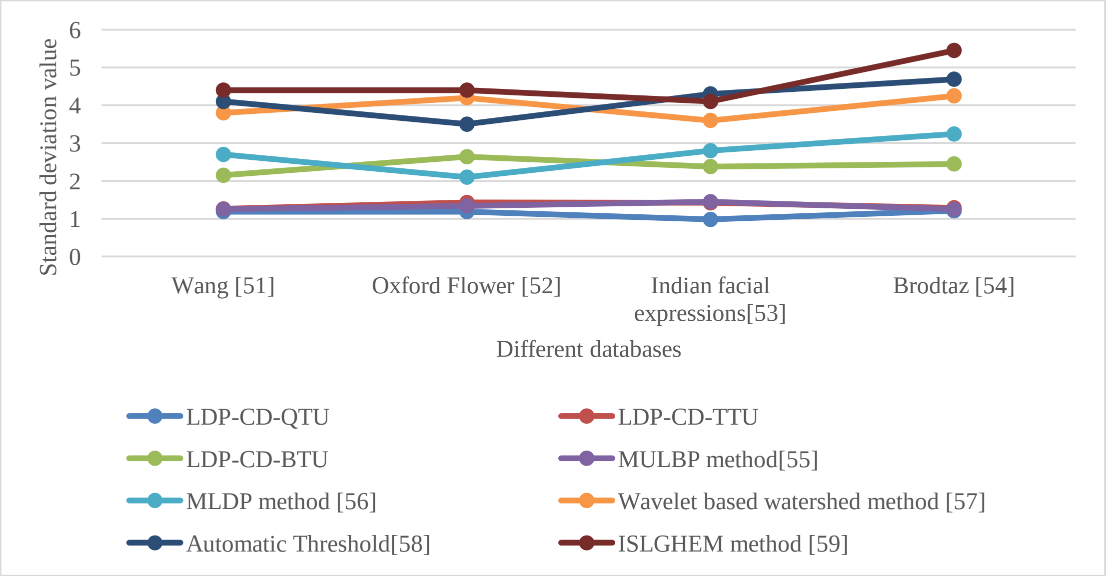

Fig. 16: Standard deviation graph of considered segmentation methods.

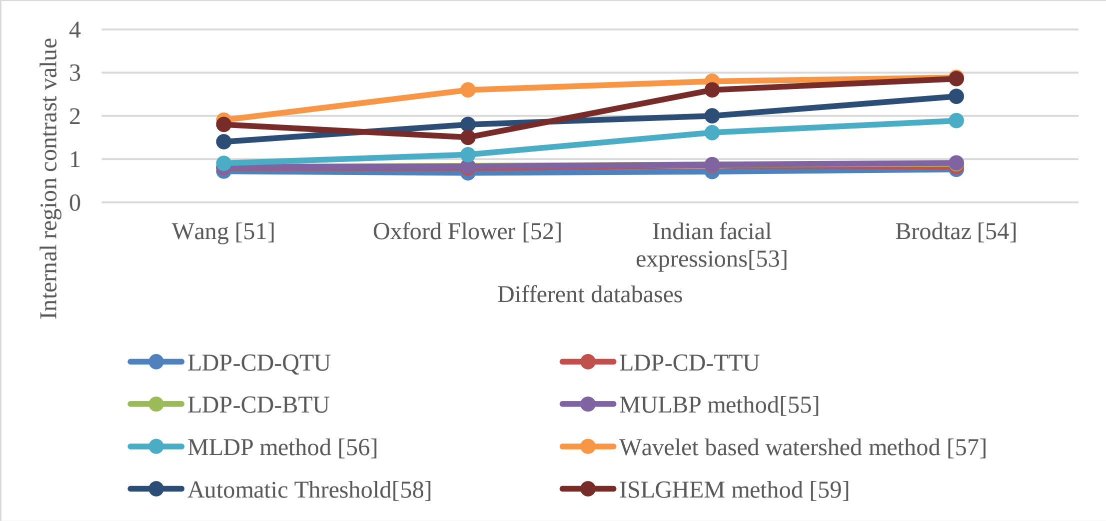

Fig. 17: Internal region contrast graph of considered segmentation methods.

5. CONCLUSIONS

The present paper proposed three categories of segmentation models on LDP based images. The present paper partitioned the 3x3 neighborhood in to cross and diagonal TU's to reduce the dimensionality of the original TUs. These dimensionalities of the proposed three categories of CTU and DTU are listed in table 1. There is a huge reduction of dimensionality with more significant and precise performance. The proposed LDP-CD-BTU resulted with a very low average discrepancy value around 29.98, average entropy value of 0.75 (indicating very low under segmentation), an average high standard deviation and high internal region contrast of 2.41 and 0.86 clearly indicates the very poor segmentation. The reason for poor segmentation for the LDP-CD-BTU is, it is dividing the neighborhood pixels into two values without any threshold and in such case the concept of further splitting or micro levels of the neighborhood completely degrades the overall performance. To improve the LDP-CD-BTU and the basic TU performance, the present paper derived threshold based LDP-CD-TTU and LDP-CD-QTU . The LDP-CD-TTU has shown an average value of 31.71, 0.81, 1.35 and 0.82 for discrepancy, entropy, standard deviation and internal region contrast respectively. The proposed LDP-CD-TTU exhibited high segmentation performance than the existing segmentation methods [55, 56, 57, 58, 59].The LDP-CD-QTU has shown a very high discrepancy average value of 27 and among the four databases considered the Indian facial expression database has shown a value of 33.1. The LDP-CD-QTU has shown an average entropy value of 1.36 and all considered databases exhibited a decent segmentation without any over and under segmentations. The average standard deviation and internal region contrast value of LDP-CD-QTU are 1.14 and 0.72 respectively indicates the formation of high uniform regions by the proposed segmentation approaches. The average performance of the LDP-CD-QTU is very high when compared to all other existing methods [55, 56, 57, 58, 59] and the other proposed segmentation methods. This is mainly because of the threshold that divides the neighboring pixels into quinary texture elements and the formation of cross and diagonal micro texture units.

6. REFERENCES

[1] M. Pietika¬ inen, A. Rosenfeld, "Image segmentation by texture using pyramid node linking", IEEE Trans. Systems Man Cybernet. 11 ,1981, 822-825

[2] P.C. Chen, T. Pavlidis, "Segmentation by texture using a co-occurrence matrix and a split-and-merge algorithm", Comput. Graphics Image Processing 10 (1979) 172-182.

[3] M. Spann, R. Wilson, "A quad-tree approach to image segmentation which combines statistical and spatial information", Pattern Recognition, 18 (1985) 257-269.

[4] L.S. Davis, A. Mitiche, Mites: "A model driven, iterative texture segmentation algorithm", Comput. Graphics Image Processing 19 (1982) 95-110.

[5] J.Y. Hsiao, A.A. Sawchuk, "Unsupervised texture image segmentation using feature smoothing and probabilistic relaxation techniques", Computer Vision Graphics Image Processing 48 (1989) 1-21.

[6] M. Unser, M. Eden, "Multiresolution feature extraction and selection for texture segmentation", IEEE Trans. Pattern Anal. Machine Intelligence 11 (1989) , 717-728

[7] H. Deng and D.A. Clausi, "Gaussian MRF rotation-invariant features for image classification", IEEE Trans. PAMI, vol. 26, pp. 951-955, 2004

[8] J. Mao, A.K. Jain, "Texture classification and segmentation using multi resolution simultaneous autoregressive models", Pattern Recognition 25 (1992) 173-188

[9] B.B. Chaudhuri, N. Sarkar, "Texture segmentation using fractal dimension", IEEE Trans. Pattern Anal. Machine Intelligence, 17 (1995) 72-77

[10]] H. Greenspan, R. Goodman, R. Chellappa, C.H. Anderson, "Learning texture discrimination rules in a multiresolution system", IEEE Trans. Pattern Anal. Machine Intelligence 16 (1994) 894-901

[11] S. Arivazhagana, L. Ganesanb, Texture segmentation using wavelet transform, Pattern Recognition Letters , Volume 24, Issue 16, December 2003, Pages 3197–3203.

[12] J.-L. Chen, A. Kundu," Unsupervised texture segmentation using multichannel decomposition and hidden Markov models", IEEE Trans. Image Processing, 4 (1995), 603-619.

[13] D.K. Panjwani, G. Healey, "Markov random field models for unsupervised segmentation of textured color images", IEEE Trans. Pattern Anal. Machine Intelligence, 17 (1995), 939-954.

[14] Mairal, J., Leordeanu, M., Bach, F., Hebert, M., Ponce, J.: "Discriminative sparse image models for class-specific edge detection and image interpretation". Proc. 10th European Conf. Computer Vision, 2008, pp. 43–56.

[15] Arbelaez, P., Maire, M., Fowlkes, C., Malik, J.: "Contour detection and hierarchical image segmentation", IEEE Trans. Patt. Anal. Mach. Intell., 2010, 33, (5), pp. 898–916

[16] Peng, B., Zhang, L., Zhang, D.: "Automatic image segmentation by dynamic region merging", IEEE Trans. Image Process., 2011, 20, (12), pp. 3592–3605.

[17] Jähne, B.: "Practical handbook on image processing for scientific and technical applications", (CRC Press, 2004, 2nd Ed.), Ch. 15

[18] Shi, J., Malik, J.: "Normalized cuts and image segmentation", IEEE Trans. Patt. Anal. Mach. Intell., 22, (8), 2000, pp. 888–905.

[19] Carreira-Perpinan, M.A.: ''Acceleration strategies for Gaussian mean-shift image segmentation''. Proc. IEEE Conf. on Computer Vision Pattern Recognition, Vol. 1, June-2006, pp. 1160–1167

[20] Mayer, A., Greenspan, H.: 'An adaptive mean-shift framework for MRI brain segmentation', IEEE Trans. Med. Imag., 28, (8), 2009, pp. 1238–1250

[21] Tao, W., Jin, H., Liu, J.: ''Unified mean shift segmentation and graph region merging algorithm for infrared ship target segmentation'', Opt. Eng., 2007, 46, (12), pp. 127002–127002–7

[22] Cour, T., Benezit, F., Shi, J.: ''Spectral segmentation with Multiscale graph decomposition''. Proc. IEEE Conf. on Computer Vision Pattern Recognition, vol. 2, June 2005, pp. 1124–1131

[23] Huang, S.H., Chu, Y.H., Lai, S.H., Novak, C.L.: ''Learning-based vertebra detection and iterative normalized-cut segmentation for spinal MRI'', IEEE Trans. Med. Imag., 28, (8), 2009, pp. 1595–1605

[24] Malik, J., Belongie, S., Leung, T., Shi, J.: 'Contour and texture analysis for image segmentation', Int. J. Comput. Vis., 2001, 43, (1), pp. 7–27.

[25] Yu, S.X., Shi, J.: 'Multiclass spectral clustering'. Proc. Int. Conf. Computer Vision, October 2003, pp. 313–319.

[26] Yu, S.X.: ''Segmentation induced by scale invariance''. Proc. IEEE Conf. on Comput. Vision Pattern Recognition, June 2005, vol. 1, pp. 444–451.

[27] Yu, S.X.: 'Segmentation using multiscale cues''. Proc. IEEE Conf. on Comput. Vision Pattern Recognition, June 2004, vol. 1, pp. I-247–I-254.

[28] Chen, T.W., Chen, Y.L., Chien, S.Y.: ''Fast image segmentation based on K-means clustering with histograms in HSV color space''. Proc. IEEE Int. Workshop on Multimedia Signal Processing, October 2008, pp. 322–325.

[29] Ghamisi, P., Couceiro, M.S., Benediktsson, J.A., Ferreira, N.M.: ''An efficient method for segmentation of images based on fractional calculus and natural selection'', Expert Syst. Appl., 39, (16), 2012, pp. 12407–12417.

[30] Tan, K.S., Isa, N.A.M., Lim, W.H.: 'Color image segmentation using adaptive unsupervised clustering approach', Appl. Soft Comput., 2012, 13, pp. 2017–2036.

[31] Tan, K.S., Isa, N.A.M.: ''Color image segmentation using histogram Thresholding – Fuzzy C-means hybrid approach", Patt. Recogn., 2011, 44, (1), pp. 1–15.

[32] Tan, K.S., Lim, W.H., Isa, N.A.M.: 'Novel initialization scheme for Fuzzy C-Means algorithm on color image segmentation', Appl. Soft Comput., 2013, 13, pp. 1832–1852.

[33] T. Ojala, M. Pietika inen, D. Harwood, " A comparative study of texture measures with classiÞcation based on feature distributions", Pattern Recognition,29,1996 ,51-59

[34] D. Harwood, T. Ojala, M. Pietika¬ inen, S. Kelman, L.S. Davis, "Texture classiÞcation by center-symmetric auto-correlation, using Kullback discrimination of distributions", Pattern Recognition Lett. 16 (1995) 1-10

[35] T. Ojala, M. Pietika¬ inen, J. Nisula, "Determining composition of grain mixtures by texture classiÞcation based on feature distributions", Int. J. Pattern Recognition Artif. Intelligence, 10 (1996) ,73-82

[36] T. Ojala, "Multichannel approach to texture description with feature distributions, Technical Report", CAR-TR-846, Center for Automation Research, University of Maryland, 1996

[37] .Eswara Reddy, P.Chandra Sekhar Reddy, V.Vijaya Kumar, Texton based shape features on local binary pattern for age classification, International journal of image, graphics and signal processing (IJIGSP), Vol. 7, No.4,pp.54-60, July-2012

[38] Vijaya Kumar V, Jangala. Sasi Kiran, G.S.Murthy, "Pattern based dimensionality reduction model for age classification", International journal of computer applications (IJCA) ", Vol.79, No.13, , Oct-2013, pp. 14-20.

[39] Gorti S Murty, V.Vijaya Kumar, A. Obulesu, "Age classification based on simple LBP transitions", International journal of computer science and engineering (IJCSE), Vol.5, No. 10, OCT-2013, pp.885-893.

[40] P.J.S. Kumar , V. Venkata Krishna ,V.Vijaya Kumar, "A Dynamic Transform Noise Resistant Uniform Local Binary Pattern (DTNR-ULBP) for Age Classification", International Journal of Applied Engineering Research ISSN 0973-4562 Volume 11, Number 1 (2016), pp 55-60.

[41] P.Viala, M.J. Jones, Robust real time face detection, Int. J. Comput. Vis.57 (2),(2004), 2063-2077.

[42] K. Srinivasa Reddy, V.Vijaya Kumar, B.Eshwara reddy, Face Recognition based on Texture Features using Local

Ternary Patterns", I.J. Image, Graphics and Signal Processing, 2015, 10, 37-46 , ISSN: 2074-9082.

[43] V Vijaya Kumar, U S N Raju, K Chandra Sekaran, V V Krishna, Employing long linear patterns for texture classification relying on wavelets, ICGST-Graphics, vision and image processing (ICGST-GVIP), Vol.8, No.5, pp. 13-21, Jan-2009

[44]]V.VijayaKumar, Saka Kezia, I.Santi Prabha," A new texture segmentation approach for medical images", International journal of scientific & engineering research, Vol. 4, No.1, January-2013, pp.1-5.

[45] [32] Greenblum, A. ; Dept. of Biomed. Eng., Technion - Israel Inst. of Technol., Haifa, Israel ; Sznitman, R. ; Caenorhabditis Elegans "Segmentation Using Texture-Based Models for Motility Phenotyping", IEEE Transactions on Biomedical Engineering, Vol-61 , Iss-8), January 2014

[46] A Obulesu,JS Kiran, VV Kumar, Facial image retrieval based on local and regional features, IEEE- 2015 International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), 29-31 Oct. 2015, Pp:841 - 846

[47] B.S. Manjunath, W.Y. Ma, Texture features for browsing and retrieval of image data, IEEE Trans. Pattern Anal. Mach. Intell. 18 (8) (1996) 837–842.

[48] Said Jai-Andaloussi, Mathieu Lamard, Guy Cazuguel, Hamid Tairi, Mohamed Meknassi, Christian Roux, Béatrice Cochener, Content Based Medical Image Retrieval Based on BEMD: use of Generalized Gaussian Density to model BIMFs coefficients, ICGST-GVIP Journal, Volume 10, Issue 2, June 2010

[49] T. Jabid, M.H. Kabir, O. Chae, "Robust facial expression recognition based on local directional pattern", ETRJ journal 32(5)(2010), pp:784-794

[50] Wang, L. and He , D.C. Texture Classification Using Texture Spectrum,Pattern Recognition, Vol. 23, No. 8, 1990, pp. 905-910

[51] http://wang.ist.psu.edu/docs/related/

[52] http://www.robots.ox.ac.uk/~vgg/data/flowers/

[53] Vidit Jain, Amitabha Mukherjee, 2002, The Indian Face Database, http://vis-www. cs. umass. Edu /~vidit /IndianFaceDatabase/

[54] http://www.ux.uis.no/~tranden/brodatz.html

[55] Anuradha.S.G] , K.Karibasappa 2 , B.Eswara Reddy, A Segmentation Scheme Based On Uniform LBP And Morphological Approach, Graphics, Vision and Image Processing Journal, ISSN 1687-398X, Volume 16, Issue 1, ICGST, June 2016

[56] Dr.B.Eswara Reddy Anuradha.S.G, Dr. K. Karibasappa, Image segmentation based on LDP with Morphological Treatment, Journal of Theoretical and applied information Technology, Vol-90, Issu. 2, 2016

[57] Yuan Been Chen and Oscal.T.C.Chen, "Image Segmentation Method Using Thresholds Automatically Determined from Picture Contents," in Eurasip journal on image and video processing, vol.2 (9), pp. 1-16

[58] Yu-hua Chai, Li-qun Gao, and Shun Lu, Lei Tian, "Wavelet-based Watershed for Image Segmentation", in Proc. of the 6th World Congress on Intelligent Control and Automation, Dalian, China, June , 2006, pp:21 – 23..

[59] Saka.Kezia, Dr.I.Santi Prabha, Dr.V.VijayaKumar, A New Texture Segmentation Approach for Medical Images, International Journal of Scientific & Engineering Research, Volume 4, Issue 1, January-2013

7. AUTHOR PROFILE

Mr. K.Venkata Subbaiah currently working as Assoc. Prof. in Dept. of CSE, PBR Visvodaya Institute of Technology & Science, Kavali, A.P., India. He has completed MCA from University of Madras in April, 1997 and received M.E (CSE) in April 2006, from Satyabhama University, Chennai. He is pursuing Ph.D. in Computer Science in Rayalaseema University, Kunrool, A.P., under the guidance of Dr. V.Vijay Kumar, Dean Dept. of CSE & IT and Director for Centre for Advanced Computational Research (CACR) Anurag Group of Institutions (AGI), Hyderabad, India.

Dr. V. Vijaya Kumar is working as Dean in Dept. of CSE & IT, chairman Board of studies for CSE and IT and Director Centre for Advanced Computational Research (CACR) at Anurag Group of Institutions, (AGOI) (Autonomous), Hyderabad. He received integrated M.S.Engg, in CSE from USSR in 1989. He received his Ph.D. degree in Computer Science from Jawaharlal Nehru Technological University (JNTU), Hyderabad, India in 1998 and guided 29 research scholars for Ph.D. He acted as principle investigator for various R&D projects. He published more than 110 research publications till now in various national, international journals and conferences. . His research interests include big data, image analytics, image processing, pattern recognition, digital water marking and cloud computing.