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

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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_0, n_1, n_2, \ldots, n_7\}, where \(n_0\) and \(n_8\) to \(n_7\) represents the intensity values of the central and neighboring pixel and \(n_i(0 \leq i \leq 7)\). The LBP initially derives binary patterns for the neighborhood pixels based on a threshold as given in equation 1.

\[
b_i = \begin{cases} 
0 & \Delta p_i \geq 0 \\
1 & \Delta p_i < 0 
\end{cases} 
\quad i = 0 \text{ to } 7
\]

where \(\Delta p_i = n_i - n_0\), and i= 0 to 7

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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.

\[ LBP_{p,r} = \sum_{i=0}^{n-1} b_i \times 2^i \] (2)

This LBP code replaces the central pixel. By repeating this on entire image in overlapped manner the image is converted into 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 problem and to capture local texture information the present research computes edge response values in eight directions of a particular pixel based on Kirsch masks in eight different orientations (M<sub>0</sub>-M<sub>7</sub>). These masks are shown in Fig.3. Eight edge response values will be obtained (m<sub>0</sub>, m<sub>1</sub>…m<sub>7</sub>) from these m<sub>0</sub> to m<sub>7</sub>. And they represent significant edges in these directions. The k-most significant or top edge response values (m<sub>i</sub>/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.

\[ LDP(x,y) = \sum_{i=0}^{7} m_i \times 2^i \] (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.

![Fig.4: Transformation of LDP code for K=2 and K=3](image)

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<sub>0</sub>-M<sub>7</sub>). These masks are shown in Fig.3. Eight edge response values will be obtained (m<sub>0</sub>, m<sub>1</sub>…m<sub>7</sub>) from these m<sub>0</sub> to m<sub>7</sub>. And they represent significant edges in these directions. The k-most significant or top edge response values (m<sub>i</sub>/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.
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 LBP code by this fluctuation. This is because gradients are more stable than gray level values under and non-monotonic illumination changes.

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 LBP 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 on this based on a threshold i.e. the

\[ LDP = \begin{cases} 0 & \text{if } n_i \leq n_e \\ 1 & \text{if } n_i = n_e \text{ for } i = 0,1,2,\ldots,7 \\ 2 & \text{if } n_i > n_e \end{cases} \]  

(4)

In step two the texture unit number \( T_{U_n} \) 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 \( T_{U_n} \) as shown in equation 5.

\[ T_{U_n} = \sum_{i=0}^{7} T_i \cdot 3^i, T_i \in \{0,1,2\} \text{ and } T_{U_n} \in \{0,1,2,\ldots,3^{k-1}\} \]  

(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.

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 TU\(_n\) 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.

\[ T_i = \begin{cases} 0 & \text{if } n_i < n_c - k \\ 1 & \text{if } n_i \geq n_c - k \text{ and } n_i < n_c + k \\ 2 & \text{if } n_i \geq n_c + k \end{cases} \]  

(6)

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

\[ \text{TTU}_n = \sum_{i=0}^{7} T_i \cdot 3^i, T_i \in \{0,1,2\} \text{ and } \text{TTU}_n \leq \{0,1,2,\ldots,6561\} \]  

(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 \(3^3\) 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 \(2^3\), 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.

\[
Q_i = \begin{cases} 
0 & \text{if } n_1 < n_c \text{ and } n_1 < n_c - k \\
1 & \text{if } n_1 < n_c \text{ and } n_1 \geq n_c - k \\
2 & \text{if } n_1 = n_c \\
3 & \text{if } n_1 > n_c \text{ and } n_1 < n_c + k \\
4 & \text{if } n_1 > n_c \text{ and } n_1 > n_c + k \\
\end{cases}
\]

(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.

\[
QTU_n = \sum_{i=0}^{c-1} Q_i \cdot 5^{i/2}, Q_i \in \{0,1,2,3,4\} \text{ and } QTU_n \in \{0,1,2,\ldots,2020\}
\]

(9)

For example, the process of evaluating QTU\(_n\) from a sub image of 3x3 using a threshold 2 is shown in Fig. 8.

<table>
<thead>
<tr>
<th>90</th>
<th>130</th>
<th>145</th>
</tr>
</thead>
<tbody>
<tr>
<td>160</td>
<td>140</td>
<td>200</td>
</tr>
<tr>
<td>100</td>
<td>140</td>
<td>250</td>
</tr>
</tbody>
</table>

QTU\(_n\) = 1292

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

<table>
<thead>
<tr>
<th>Existing TU</th>
<th>Proposed CDTU</th>
</tr>
</thead>
<tbody>
<tr>
<td>Binary TU</td>
<td>Ternary TU</td>
</tr>
<tr>
<td>256</td>
<td>6562</td>
</tr>
</tbody>
</table>

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.

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

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 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.
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.
5. CONCLUSIONS
The present paper proposed three categories of segmentation models on LDP based images. The present paper partitioned the 3x3 neighborhood into 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 indicating 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 unary texture elements and the formation of cross and diagonal micro texture units.

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