# Tri-Octet Local Neighborhood Difference Pattern: A new feature descriptor for natural and texture image retrieval

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***Abstract*—a new image retrieval technique using Tri-Octet local neighborhood difference pattern (TO-LNDP) has been proposed for local features. The conventional local binary pattern (LBP) transforms every pixel of image into a binary pattern based on their relationship with neighboring pixels. The proposed feature descriptor differs from local binary pattern as it transforms the mutual relationship of all neighboring pixels in a binary pattern. In the proposed work, three octets forming LNDP features are combined to extract the most of the information that can be captured using local intensity differences. To prove the excellence of the proposed method, experiments have been conducted on four different databases of texture images and natural images. The performance has been observed using well-known evaluation measures, precision and recall and compared with some state-of-art local patterns. Comparison shows a significant improvement in the proposed method over existing methods.**

***Index Terms*— Tri-octet Local Neighborhood Difference Patterns, Binary Patterns, Content Based Image Retrieval, Texture Features**

## I. Introduction

A wonderful saying that 'A picture is worth a thousand words', is one of the reasons that images are extensively used in different fields, e.g., education, media, medical, etc. Databases of offline as well as online images are getting spacious over time. Image classification, searching and retrieval are strenuous and inconvenient tasks for these databases. Content based image retrieval is a technique to search similar images corresponding to a query image using the contents of image.

## II. Motivation

Many methods have been proposed for image feature extraction in content based image retrieval. Image retrieval with many categories of images, is crucial and challenging issue of the present technical world. Researchers have proposed image feature extraction methods using local intensity features. Many methods based on local neighborhood image pixels have been proposed that create features based on center and neighboring pixels relationship. In the local feature extraction, the closest neighboring pixels play important role.

The main motivation of the presented work is to provide a powerful local feature descriptor using local intensity values of pixels that extracts information based on mutual relationship of neighboring pixels and integrates the features based on the closest neighboring pixels to the center pixel.

## III. Related Work

Texture is a salient feature in image that has been widely used in image matching and recognition. Many methods have been proposed for texture classification using global and local features, transformation and spatial domain features, etc. Gray level co-occurrence matrix was proposed by Haralick et al. for image classification, and further used for texture feature analysis broadly. Discrete wavelet transforms, Gabor features, and rotated wavelet filter, rotated complex wavelet filter and dual tree complex wavelet transform were used as transformation domain feature extraction techniques in image retrieval, classification and indexing. Ojala et al. proposed local binary pattern which extracts image features based on local intensity of pixels. It has been widely used in texture features for content based image retrieval and other pattern recognition application, e.g., face recognition palm-print recognition, object tracking, etc. LBP was converted into uniform and rotation invariant pattern based on the structure of a pattern. Local binary pattern is sensitive to noise. To improve this, local ternary pattern was proposed using a threshold interval for center and neighboring pixels. Further, ternary pattern has been split into two binary patterns for histogram formation. Local derivative pattern was proposed as second and higher order LBP. Instead of center pixel and neighboring pixel relationship, center symmetric pixels were compared for pattern formation and called center symmetric local binary pattern (CSLBP). CSLBP was extended in center symmetric local binary co-occurrence pattern (CSLBCoP) using co-occurrence of pixel pairs in different directions and distances of GLCM. Dimensionality has been reduced in CSLBP pattern by merging symmetric patterns LBP considers all patterns with equal weights irrespective of importance. Liaoetal proposed dominant local binary pattern (DLBP) which extracts dominant patterns from LBP. Feature descriptor named local bit-plane decoded pattern (LBDP) has been proposed using the difference of center pixel's intensity value with the local bit-plane transformed values which are computed from the bit-plane binary contents of its each neighboring pixel. Further, many extensions of LBP, e.g., local edge pattern for segmentation and image retrieval (LEPSEG and LEPINV), local Gabor binary pattern histogram sequence (LGBPHS), completed local binary pattern (CLBP) , multi-structure local binary pattern (Ms-LBP) , etc. have been proposed.

## IV. LOCAL PATTERNS

### A. Local Binary Pattern

Local binary pattern (LBP) has been proposed by Ojala et al. for local information of pixels in an image. In this method, all pixels of image are considered as center pixel, and local information is extracted for each pixel that depends on neighboring pixels. Each center pixel is subtracted from all neighboring pixels, and a binary number is assigned to each neighboring pixel that depends on the difference of center pixel and neighboring pixel. These binary numbers construct the local binary pattern for each center pixel. Further, local binary patterns are multiplied by some weights and summed up to a pattern value that is called local binary pattern value for a center pixel. For a center pixel Ic and neighboring pixels In (n=1,2,..,8), LBP can be computed as follows:

$$\mathrm{LBP}_{P,R}(x,y) = \sum_{n=0}^{P-1} 2^n \times F_1(I_n - I_c)$$

$$F_1(I) = \begin{cases} 1 & I \geq 0 \\ 0 & \text{else} \end{cases}$$

Where R and P are the radius of neighboring pixels and number of neighboring pixels considered for pattern formation respectively. Pair (x, y) are the coordinates of center pixel. A demonstration of LBP on a 3×3 window have been shown in Fig. 1 to explain above process. After getting the LBP map of image, histogram is obtained using the following equation:

$$His(l)\ |_{\mathrm{LBP}} = \sum_{x=1}^{m}\sum_{y=1}^{n} F_2(\mathrm{LBP}(x,y), l);\ l \in [0, (2^P - 1)]$$

$$F_2(a,b) = \begin{cases} 1 & a = b \\ 0 & \text{else} \end{cases}$$

Where size of image is m×n, andl is the pattern value in the local binary pattern.

### B. Local neighborhood difference pattern

A new feature extraction method called local neighborhood difference pattern (LNDP), has been proposed in the present work. As it appears from its name, this method extracts the local features based on neighborhood pixel differences and form a binary pattern to represent each pixel in the image. For each pixel, a 3×3 block has been chosen for pattern calculation as the closest neighboring pixels are less in number and give more related information. Each neighboring pixel in the block is compared with two most adjacent and appropriate pixels. These two neighborhood pixels are either vertical or horizontal pixels as they are the closest to the considered neighboring pixel. Relationship of these two pixels has been obtained with neighboring pixel, and a binary number is assigned. Similarly, for each neighboring pixel a binary number is obtained. Pattern of these binary numbers is formed to represent each pixel, and finally, histogram is constructed to represent the image in a form of LNDP. For neighboring pixels In (n=1,2,..,8) of a center pixel Ic, LNDP can be computed in the following procedure:

$$k_1^n = I_8 - I_n,\ k_2^n = I_{n+1} - I_n, \quad for \quad n = 1$$

$$k_1^n = I_{n-1} - I_n,\ k_2^n = I_{n+1} - I_n, \quad \forall \quad n = 2, 3, .., 7$$

$$k_1^n = I_{n-1} - I_n,\ k_2^n = I_1 - I_n, \quad for \quad n = 8$$

Difference of each neighborhood pixel with two other neighborhood pixels have been obtained in kn1 and kn2. Based on these two differences, a binary number is assigned to each neighboring pixel.

$$F_3(k_1^n, k_2^n) = \begin{cases} 1,\ if & k_1^n \geq 0 \quad \& \quad k_2^n \geq 0 \\ 1,\ if & k_1^n < 0 \quad \& \quad k_2^n < 0 \\ 0,\ if & k_1^n \geq 0 \quad \& \quad k_1^n < 0 \\ 0,\ if & k_1^n < 0 \quad \& \quad k_2^n \geq 0 \end{cases}$$

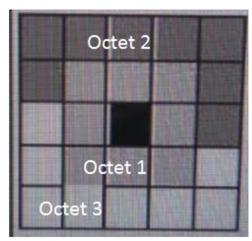
For the center pixel Ic, LNDP can be computed using above binary values as follows:

$$LNDP(I_c) = \sum_{n=1}^{8} 2^{n-1} \times F_3(k_1^n, k_2^n)$$

Histogram for LNDP map can be achieved as follows:

$$His(l)\ |_{\mathrm{LNDP}} = \sum_{x=1}^{m}\sum_{y=1}^{n} F_2(\mathrm{LNDP}(x,y), l);\ L \in [0, (2^8 - 1)]$$

This same procedure is used to produce three octets for each pixel. Histogram of these three features of each image are concatenated into a whole and that is used as the feature descriptor. The three octets for each pixel are chosen as follows:




## V. PROPOSED SYSTEM FRAMEWORK

### A. Similarity Measure

To compute the similarity between two images, feature vectors are extracted, and distance between feature vectors are computed. Distance that is used here is Manhattan distance. For a given query image q and a database image db.

Dis(db,q)= Sum ( abs ( Fdb,Fq) ); (1)

where Fdb and Fq are feature vectors of database image and query image respectively. Minimum distance shows the maximum match between two images.

### B. Algorithm

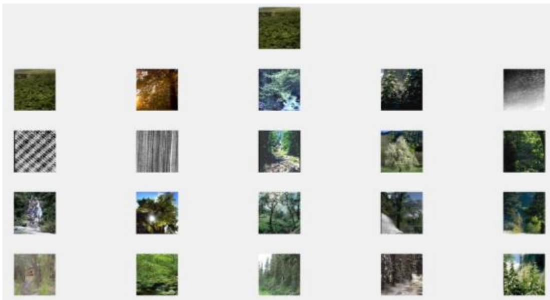
Algorithm for our project implementation is given below:

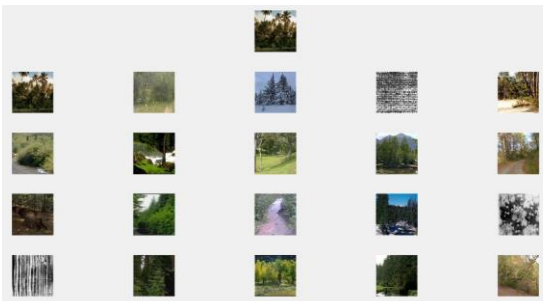
1. Upload the image and convert it into a gray scale image if it is a color image.
2. Compute local binary pattern of the image.
3. Compute local neighborhood difference pattern of the image.
4. Create histograms of LBP and LNDP maps.
5. Concatenate both histograms as feature descriptor.

6. Compute the distance of the query image feature vector with all database image feature vectors using (1).

## VI. Results

Precision of the system is 90% aprox.





## VII. Conclusion

In the presented work, a novel local feature descriptor has been proposed and named as Tri-Octet local neighborhood difference pattern (TO-LNDP). The proposed local feature descriptor, TO-LNDP, is a complementary method over LBP as it extracts the relationship among neighboring pixels by comparing them mutually. On the contrary, LBP computes the relationship of neighboring pixels with center pixel. The proposed method has been applied in content based image retrieval of texture and natural image datasets. The proposed feature descriptor extracts features based on the texture, hence, it can be utilized for texture feature based image recognition systems, e.g., palmprint, fingerprint, knuckle print, leaf, iris, etc. The proposed feature descriptor can be utilized with an appropriate region detector for object or region-specific image retrieval and scene recognition problem.

## VIII. References


1. Ahmadian A, Mostafa A (2003) An efficient texture classification algorithm using gabor wavelet. In: Proceedings of 25th annual international conference of engineering in medicine and biology society, vol 1. IEEE, Cancun, Mexico, pp 930–933
2. Ahonen T, Hadid A, Pietikainen M (2004) Face recognition with local binary patterns. In: Proceed-¨ ings of 8th European conference on computer vision. Springer, Prague, Czech Republic, pp 469– 481
3. Baber J, Satoh S, Afzulpurkar N, Bakhtyar M (2012) Q-CSLBP: compression of CSLBP descriptor. In: Advances in multimedia information processing–PCM. Springer, Singapore, pp 513–521
4. Bay H, Tuytelaars T, Van Gool L (2006) Surf: Speeded up robust features. In: European conference oncomputer vision. Springer, pp 404–417
5. Celik T, Tjahjadi T (2009) Multiscale texture classification using dual-tree complex wavelet transform.Pattern Recogn Lett 30(3):331–339
6. Dalal N, Triggs B (2005) Histograms of oriented gradients for human detection. In: Internationalconference on computer vision and pattern recognition, vol 1. IEEE, pp 886–893
7. Dubey SR, Singh SK, Singh RK (2015) Local diagonal extrema pattern: a new and efficient featuredescriptor for ct image retrieval. IEEE Signal Process Lett 22(9):1215–1219
8. Dubey SR, Singh SK, Singh RK (2015) Local neighbourhood-based robust colour occurrence descriptorfor colour image retrieval. IET Image Process 9(7):578–586
9. Dubey SR, Singh SK, Singh RK (2016) Local bit-plane decoded pattern: A novel feature descriptor forbiomedical image retrieval. IEEE J Biomed Health Inform 20(4):1139–1147
10. Guo Z, Zhang L, Zhang D (2010) A completed modeling of local binary pattern operator for textureclassification. IEEE Trans Image Process 19(6):1657–1663
11. Haralick RM, Shanmugam K, Dinstein IH (1973) Textural features for image classification. IEEE TransSyst Man Cybern 3(6):610–621
12. He Y, Sang N, Gao C (2013) Multi-structure local binary patterns for texture classification. Pattern AnalAppl 16(4):595–607
13. Heikkila M, Pietik¨ ainen M, Schmid C (2006) Description of interest regions with center-symmetric¨ local binary patterns. In: Computer vision, graphics and image processing. Springer, Madurai, India, pp 58–69
14. Houam L, Hafiane A, Boukrouche A, Lespessailles E, Jennane R (2014) One dimensional local binarypattern for bone texture characterization. Pattern Anal Appl 17(1):179–193
15. Jeena Jacob I, Srinivasagan KG, Jayapriya K (2014) Local oppugnant color texture pattern for imageretrieval system. Pattern Recogn Lett 42:72–78
16. Kokare M, Biswas PK, Chatterji BN (2005) Texture image retrieval using new rotated complex waveletfilters. IEEE Trans Syst Man Cybern Part B Cybern 35(6):1168–1178
17. Kokare M, Biswas PK, Chatterji BN (2007) Texture image retrieval using rotated wavelet filters. PatternRecogn Lett 28(10):1240–1249
18. Li Z, Liu J, Tang J, Lu H (2015) robust structured subspace learning for data representation. IEEE TransPattern Anal Mach Intell 37(10):2085–2098
19. Li Z, Tang J (2015) Unsupervised feature selection via nonnegative spectral analysis and redundancycontrol. IEEE Trans Image Process 24(12):5343–5355
20. Liao S, Law MWK, Chung ACS (2009) Dominant local binary patterns for texture classification. IEEETrans Image Process 18(5):1107–1118
21. Liu Y, Zhang D, Lu G, Ma WY (2007) A survey of content-based image retrieval with high-levelsemantics. Pattern Recogn 40(1):262–282
22. Loupias E, Sebe N, Bres S, Jolion JM (2000) Wavelet-based salient points for image retrieval. In: Proceedings of international conference on image processing, vol 2. IEEE, BC, Canada, pp 518–521
23. Lowe DG (1999) Object recognition from local scale-invariant features. In: International conference oncomputer vision, vol 2. IEEE, pp 1150–1157
24. Ma WY, Manjunath BS (1996) Texture-based pattern retrieval from image databases. Multimed ToolsAppl 2(1):35–51
25. Mabood L, Ali H, Badshah N, Chen K, Khan GA (2016) Active contours textural and inhomogeneousobject extraction. Pattern Recogn 55:87–99
26. Mikolajczyk K, Schmid C (2005) A performance evaluation of local descriptors. IEEE Trans PatternAnal Mach Intell 27(10):1615–1630
27. Mikolajczyk K, Tuytelaars T, Schmid C, Zisserman A, Matas J, Schaffalitzky F, Van Gool L (2005) Acomparison of affine region detectors. Int J Comput Vis 65(1-2):43–72
28. Muller H., Michoux N, Bandon D, Geissbuhler A (2004) A review of content-based image retrieval¨ systems in medical applicationsclinical benefits and future directions. Int J Med Inform 73(1):1–23
29. Murala S, Maheshwari RP, Balasubramanian R (2012) Directional local extrema patterns: a newdescriptor for content based image retrieval. Int J Multimed Inf Retr 1(3):191–203
30. Murala S, Maheshwari RP, Balasubramanian R (2012) Local maximum edge binary patterns: a newdescriptor for image retrieval and object tracking. Signal Process 92(6):1467–1479

31. Murala S, Maheshwari RP, Balasubramanian R (2012) Local tetra patterns: a new feature descriptor forcontent-based image retrieval. IEEE Trans Image Process 21(5):2874–2886
32. Murala S, Wu QJ (2015) Spherical symmetric 3D local ternary patterns for natural, texture andbiomedical image indexing and retrieval. Neurocomputing 149:1502–1514