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Local Binary Patterns and Its Extended Variants

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Abstract: **This paper focuses on the Local Binary Patterns and its various important variants. LBP is a non-parametric descriptor and used to extract, analyze, recognize and classify the different modality images. It summarizes the local patterns of image characteristics efficiently. LBP and its many extended versions have been extensively used in numerous applications of computer vision, image processing, pattern recognition and biomedical field in recent years. Very discriminative and computationally efficient local texture descriptors based on local binary patterns (LBPs) is studied, which led to significant progress in applying texture methods to different problems and applications. The efficiency and usability of the LBP operator and its success in various real world applications has inspired the development of much new powerful LBP variants. In this paper, the important extensions of LBP using local structure of the image are extensively reviewed.**

Keywords**: Local Binary Pattern, Texture, LBP, LTP.**

I. INTRODUCTION

The texture of images refers to appearance, structure, arrangement of the parts of an object within the image. Images used for diagnostic purposes in clinical field are digital and most probably two dimensional. Texture analysis has been researched since the 1960. In principle it is a technique for evaluating the position and intensity of signal features that means pixels and their gray level intensities. The distribution of these pixels can be computed to produce mathematical parameters which characterize the texture type. The underlying structure of objects is shown in image. These values are also known as texture features. During that time studies showed much important information contained in the distributions of feature values were lost through the usage of these single texture measures. These texture classification methods assume that unknown samples to be classified are always identical to training samples with respect to scale, orientation and gray-scale properties. Real world textures are not like that, those are unpredictably subjected to varying illumination conditions and arbitrary spatial rotations constantly**.** This showed how unreliable past texture classifications were and their incompetence in handling real world images.

Information was first published as part of a comparative study of texture operators in the international conference on pattern recognition [1]. Not to mention, the degree of computational complexity in those algorithms was too high [2]. A very helpful suggestion for future research from then was to develop texture measures which incorporate invariance to real-world factors such as orientation and scale, and can be classified with a low-computational complexity [3].

II. LOCAL BINARY PATTERNS

LBP is introduced in 1996 as a comparative study of texture measures with classifications, pattern recognition [4]. LBP is applied in computer vision and image processing. It is used for textual and facial description. It is feature extraction descriptor. This operator acts as an image operator which transforms an image into an array or image of integer labels describing small scale appearance (textures) of image. These label directly or their statistics are used for further analysis. LBP has been found as a powerful feature for texture classification [5].

A. Grayscale image to LBP mask

To calculate the LBP descriptor, we convert the input color image to grayscale, since LBP works on grayscale images. For each pixel in the grayscale image, a neighborhood is selected around the current pixel and LBP value is calculated for the pixel using the neighborhood. After calculating the LBP value of the current pixel, we update the corresponding pixel location in the LBP mask (It is of same height and width as the input image) with the LBP value.

Given a grayscale image I of size n × m pixels and I (g) denotes the gray level of the g th pixel in the image I. The LBP operator is calculated at each pixel by evaluating the binary differences of the values in a small circular neighborhood (with radius R) around the value of a central pixel, g_c where g_c: gray value of the center pixel; g_p: gray values of the circularly symmetric neighborhood g_p (p = 0,..., P = 1); P is image pixels in the circle of radius R(R > 0); 2^P binomial factor for each sign f_1 (g_p- g_c). If there is an image I(x, y) and let g_p denote the gray value of a sampling point with coordinates Xp, Yp in an evenly spaced circular neighborhood of P sampling points and radius R around point x_c,y_c. It is expressed in equations (1), (2) and (3) as follows.

Mathematically, the LBP value of current pixel is given in figure 1, where value of LBP code of a pixel x_c,y_c is given [6].

$$g_p = I(x_p y_p),\ p = 0, \text{ to } P-1 \quad (1)$$

$$x_p = x_c + R\cos(2\pi p/P), \quad (2)$$

$$p = y_c - R\sin(2\pi p/P) \quad (3)$$

Assume that the local texture T of the image I (x, y) is characterized by the joint distribution of gray values of P+1(P >0) pixels. Moreover, let g_c denote the gray level of the local texture neighborhood [7] center pixel x_c, y_c) as in expression (4) below:

$$g_c = I(x_c, y_c):$$

$$T = t(g_c, g_0, g_1 \ldots gp_{-1}), \quad (4)$$

The value of the LBP code of a pixel (x_c,y_c) is expressed in equation (5) as given below

$$LBP_{P,R} = \sum s(g_p - g_c)\, 2^P$$

$$\{\text{Value from p=0 to P-1}\} \quad (5)$$

$$S(x) = \{1 \text{ if } x \geq 0;\ 0 \text{ if else}\}$$

For example if we have 70 as threshold value others its neighborhood values, its sample difference and threshold representation is shown in figure-1.

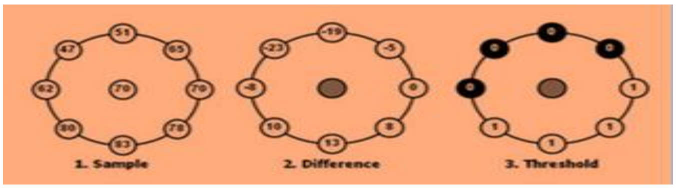

Fig.1: Sample, difference, threshold representation

B. LBP operation and procedure

The extraction of LBP operator comprises two main steps: one is thresholding and second is encoding step. The thresholding step extract the information about the local binary difference (1 or 0) by comparing the circular neighbor pixels value with central pixel in a patch of the image. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. The two-dimensional textures can be described by two complementary local measures: spatial structure (pattern) and contrast (the amount of local image texture). In terms of gray-scale and rotation invariance, these two properties are an interesting pair; spatial pattern is affected by rotation of the texture but contrast is not and contrast is affected by the gray-scale though spatial pattern is not. Therefore if a texture descriptor is capable in separating the texture's pattern information from its contrast, then invariance to monotonic gray scale changes can be obtained.

For LBP convert an image to grayscale. For each pixel in the grayscale image, a neighborhood of size r is selected; say three, surrounding the center pixel. For each pixel's three by three (3×3) neighbor, compare the center value and its neighbor values. If the neighbor can be any of the 8 neighbor values as long as it is consistent. Let LBP value to be 0 and if the binary value of the starting pixel is one, add 2^0 to the LBP value, else 0. If the next binary value is one, add 2^1, else add 0. If the next binary value is one, add 2^2, else add 0. Repeat this process until the last pixel. For example in the graph given below figure 2, setting top left corner as the starting pixel, and ordering the neighbor pixel values in clock wise manner, we can convert the binary operated values to a digit as:

$$\mathbf{141 = 2^0 + 2^2 + 2^3 + 2^7}$$

One advantage of LBP is that it is illumination and translation invariant. As 8 point neighborhood is selected but most implementations use a circular neighborhood. The original LBP algorithm has been further optimized to give better results. One such implementation is the uniform LBP. LBP is used successfully for face recognition [8]. The newly proposed texture descriptors provide a progress in texture analysis by means of their high discriminative properties and computational efficiency. LBP and its variants outperformed than other reported descriptors in the field of texture analysis based applications [9]. This operator is extended as 2D plus time voxel version of LBP [10], called VLBP, and used them successfully for facial gesture recognition. LBP features are combined with HOG features [11] to address the problem of partial occlusions in the problem of human detections.

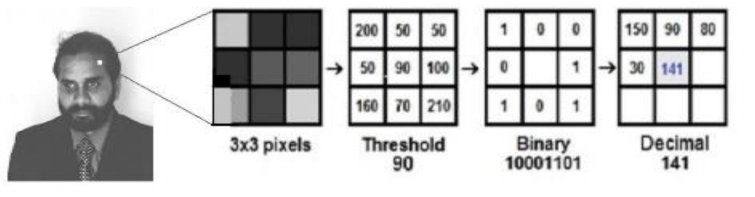

Fig. 2: LBP graph with binary values according to threshold

C. Uniform and Rotation Invariant LBP

Uniform LBP is an important case of LBP. An LBP descriptor is called uniform if it contains at most two circular bitwise 0-1 transitions. Uniformity measure U (pattern) is the number of bitwise transitions from 0 to 1 or vice versa. A local binary pattern is called uniform if its uniformity measure is at most 2. That is transitions between 0 and 1 ≤ 2. Since allotted binary string needs to circulate, the occurrence of only one transition is not possible. This means a uniform pattern has no transition or two transitions. There are main reasons for considering only uniform pattern, one that in real world scenario most of the texture have uniform in nature and themselves are more stable i.e. less affected by noise and another reason is, because only consider uniform pattern so the minimum samples of LBP are reliable to recognized the texture pattern [12].

ROR(x,i) represents circular bitwise right rotation of x by i steps. 8-bit LBP codes 10000010b, 00101000b, and 00000101b all map to the minimum code 00000101b.

III. EXTENDED LOCAL BINARY PATTERNS

There are many different forms of local binary patterns which are studied, analyzed for different application in many fields. These are reviewed here.

A. Complete Local Binary Pattern (CLBP)

Complete Local Binary Pattern is a typical local binary pattern operator that only considers the local features of an image and global features are neglected. To improve the performance of LBP by considering global thresholding and a new approach named as complete local binary pattern is explained in [13]. The image descriptor splits into two complementary components: sign and magnitude component as shown in equation (6) as given below.

$$s_p = s(w_p - w_c), \quad m_p = |w_p - w_c| \qquad (6)$$

s_p is sign and m_p is used to build the magnitude component of CLBP_S and CLBP_M respectively. CLBP_S is the same to traditional LBP operator while in CLBP_M the local variance of the magnitude is calculated. These two components can be described mathematically in equation (7) and (8) as given below.

$$CLBP\_S_{P,R} = \sum 2^p s(w_p - w_c),$$

$$\text{For P=0 to P=1} \qquad (7)$$

$$S = \{0 \text{ if } w_{p \le} w_c, \ 1 \text{ if } w_p = w_c\} \qquad (8)$$

Here w_c, w_p and p are defined, *c* in equation denote mean value of magnitude component in whole image. The authors calculated the global features by using center pixel as threshold and coded into binary format. This operator called CLBP Center. The CLBP_C can be defined mathematically in the following expression in equation (9):

$$CLBP\_C_{P,R} = t(w_c, c_i) \qquad (9)$$

Where w_c is the center pixels value and c_i is the average gray level of the whole image [14]. The calculated features from these operators can be combined into joint histogram for final texture classification.

B. Local Ternary Patterns (LTP)

The result of LBP algorithm is grounded on L=2, means binary number operation by specifying the center pixel intensity value as a threshold. As the threshold value is center pixel, this is the main reason that LBP descriptor is more sensitive to noise specially for smooth regions of images. To overcome the noise sensitivity problem an interesting abstraction of LBP is known as Local Ternary Pattern [15]. LTP three quantization levels are used to encode the difference between central pixel and its neighbor to a threshold. The threshold value is set to be manually and its value depends in order to attain the best performance in specific problems and applications. One of main limitation in LBP descriptor as appeared that LBP is in the image. The reason behind this is that LBP is very sensitive to the noise with the central pixel as threshold value. Same limitation comes in LBP variants such as in complete local binary pattern.

C. Complete Local Ternary Pattern (CLTP)

A new diversion was proposed [16], in which it is introduce the global features in LTP as similar to CLBP and named as complete local ternary pattern. The local difference of an image was further decomposes into two sign and two magnitude components.

D. Improved Local Ternary Pattern (ILTP)

The modified version of LTP that is known as improved local ternary pattern [17] is introduced to reduce the sensitivity of noise in central pixels because it is used as threshold to encode. The method is based on replacement of central pixel value with the average value of a patch or region.

E. Local Adaptive Ternary Pattern (LATP)

In the original LTP operator the value of threshold need to be set manually. It is very critical task to set a threshold value for calculating all local patches in order to reduce the sensitivity to noise for different applications. Local adaptive ternary pattern [18] is proposed, in which the threshold value is set with automatic adaptive procedure by using local statistics as a mean value and standard deviation. To deal with threshold value problem issue, recently noticeable extensions of LTP known as Improved Local Ternary Pattern, Local Adaptive Ternary Pattern, Enhanced Local Ternary Pattern and Dynamic Local Ternary Pattern are proposed. These are based on some automatic phenomena to set threshold value for every region.

F. Center Symmetric Local Binary Patterns (CS_LBP)

The center symmetric local binary pattern is a modified version of the well-known LBP feature. Instead of comparing each pixel with center pixel [19] have compared center-symmetric pairs of pixels for CS_LBP as shown in equation (10) given as below.

$$CS\_LBP_{P,\,R} = P \sum 2^{p-1} \times f1\,(I(g_p) - I(g_p + (P/2))) \quad \text{(value from } p=1 \text{ to } P) \tag{10}$$

after computing the CS_LBP pattern for each pixel (j, k), the whole image is represented by building a histogram similar to LBP.

G. Local Configuration Patterns (LCP)

LCP descriptor is used for texture image description by combining information with LBP [20]. The descriptor provides the information of images in two parts as local structural information and MiC information that involves image configuration and pixel-wise interaction relationships. LBP is used to extract the local structural information and construct pattern occurrence histograms of images, whereas MiC information is explored by encoding linear relationships among neighboring pixels. Existing local binary pattern detects the local structures, such as lighting spots and edges in images, whereas the local configuration pattern (LCP) explores multi-channel discriminative information of both the MiC and local structures of images. Both methods are used to extract the rotation- and scale-invariant features from all lung cancer images [21].

H. Directional Local Extrema Patterns (DLEP)

This method differs from existing LBP in fact, that it extracts the directional edge information based on local extrema in 0°, 45°, 90° and 135° directions in an image. The idea of LBP has adopted to define directional local extrema patterns [22]. It describes the spatial structure of the local texture using the local extrema of center gray pixel g_c. In proposed DLEP for a given image the local extrema in 0°, 45°, 90° and 135° directions are obtained by computing local difference between the center pixel and its neighbors as shown in equation (11) below.

$I' = (g_i) = I(g_c) - I(g_i); \; i = 1, 2, ..8. \quad (11)$

The local difference between the center pixel and its eight neighbors are used to evaluate the directions. These directions are utilized to obtain DLEP patterns in 0°, 45°,90° and 135° directions. In DLEP 3×3 pattern for DLEP pair of neighbors in a local region along a given direction are selected, while LBP extracts relation between the center pixel and its neighbors. Therefore, DLEP captures more spatial information as compared to LBP. Its performance is compared with LBP, block-based LBP (BLK_LBP), center-symmetric local binary pattern (CS-LBP), local edge patterns for segmentation (LEPSEG). It is proved that directional features are very valuable for image retrieval applications [23].

I. Local Phase Quantization (LPQ)

LQP features are very similar in essence to LBPs, as the local image texture is again encoded using binary strings [24]. In texture classification problem LPQ gains better performance than LBP methods, particularly when working with blurred images. Due to high representational ability local texture descriptors-based method have been used in many fields of computer vision, among them are LBP, local phase quantization and binarized statistical image feature. The reason for employing local texture descriptors for palm print recognition is the possibility of treating the palm print image as micropatterns compositions that are properly characterized by such descriptors.

J. Local Tetra Patterns (LTrP)

Local tetra pattern is a novel image indexing and retrieval algorithm. By applying local tetra patterns for content-based image retrieval (CBIR) [25], the standard LBP and local ternary pattern encode the relationship between the referenced pixel and its surrounding neighbors by computing gray-level difference. This method encodes the relationship between the referenced pixel and its neighbors, based on the directions that are calculated using the first-order derivatives in vertical and horizontal directions. A generic strategy is proposed to compute n-th order LTrP using (n-1)th order horizontal and vertical derivatives for efficient CBIR. The effectiveness of algorithm analyzed by combining it with the Gabor transforms. The performance of proposed method is compared with LBP and local derivative patterns. The LTP based on the results provided better average retrieval rate as compared to standard LBP.

K. Local Maximum Edge Binary Patterns (LMEBP)

This algorithm is meant for content based image retrieval (CBIR) and object tracking applications. LMEBP differs from the existing LBP in a manner that it extracts the information based on distribution of edges in an image. The local region of image is represented by local maximum edge binary patterns, which are evaluated by taking into consideration the magnitude of local difference between center pixel and its neighbors. The effectiveness of this algorithm is performed [26] and confirmed by combining it with Gabor transform. Four experiments were carried out to prove the worth of this algorithm. Out of which three are meant for CBIR and one for object tracking. The results after investigation it showed significant improvement as compared to LBP and other existing transform domain techniques. LMEBP extracts more edge information as compared to existing LBP. Many extended versions of LBP are proposed in [27] and [28] to derive new image features for biomedical image indexing and retrieval.

L. Local Ternary Co-occurrence Patterns (LTCoP)

This technique is a novel feature extraction algorithm for biomedical image retrieval. The LTCoP encodes the co-occurrence of similar ternary edges, which are calculated based on gray values of center pixel and its surrounding neighbors. The standard local derivative patterns (LDP) encode the co-occurrence between the first-order derivatives in a specific direction. The existing LDP is a specific direction rotational variant feature, whereas the method is a rotational invariant. The effectiveness of the algorithm is confirmed by combining it with the Gabor transform as performed in [29]. Experiments have been carried out the investigated results showed a significant improvement as compared to LBP, LTP, local tetra patterns (LTrP) and LDP.

M. Local Mesh Patterns (LMP)

The new image indexing and retrieval technique using the local mesh patterns are proposed for biomedical image retrieval application. Standard local binary pattern encodes the relationship between the referenced pixel and its surrounding neighbors, whereas local mesh pattern encodes a relationship among the surrounding neighbors for a given referenced pixel in an image. The possible relationships among the surrounding neighbors depend upon the number of neighbors. The effectiveness of algorithm [30] is confirmed by combining it with the Gabor transform. To prove the effectiveness of algorithm, the three experiments on three different biomedical image databases are performed. The results showed significant improvement as compared to LBP, LBP with Gabor transform, and other spatial and transform domain methods.

N. Local Extrema Co-occurrence Patterns (LECoP)

Local extrema co-occurrence pattern is a new image retrieval technique which uses the HSV color space. HSV color space is used in this method to utilize the color, intensity and brightness of the images. Local extrema patterns are applied to define the local information of image. The gray level co-occurrence matrix is used to obtain the co-occurrence of LEP map pixels [31]. The local extrema co-occurrence pattern extracts the local directional information from local extrema pattern. Then convert it into a well-mannered feature vector with use of gray level co-occurrence matrix.

O. Directional Local Ternary Quantized Extrema Patterns (DLTerQEP)

The DLTerQEP is disparate from the familiar LBP method. LBPs and local ternary patterns (LTPs) encode the gray scale relationship between the center pixel and its surrounding neighbors in two dimensional (2D) local region of an image. The proposed method [32] encodes the spatial relation between any pair of neighbors in a local region along the given directions (i.e. 0°, 45°, 90° and 135°) for a given center pixel in an image. It uses ternary patterns from Horizontal Vertical Diagonal Anti-diagonal (HVDA7) structure of directional local extrema values of an image to encode more spatial structure information. DLTerQEP extracts the spatial relation between any pair of neighbors in a local region along the given directions, while LBP extracts relation between the center pixel and its neighbors. It take out directional edge information based on local extrema that differ it from the existing LBP [32]. DLTerQEP provides a significant increase in discriminative power by allowing larger local pattern neighborhoods.

P. Local Derivative Patterns (LDP)

A novel method for texture classification using high-order local pattern descriptor is 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. The global textural aspect of an image is revealed by its texture spectrum. LBP provides the first-order directional derivative patterns but in [33], it is examined that LBP acts as non-directional first-order local patterns and have proposed local derivative patterns for face recognition. Both LBP and LDP cannot appropriately find out the appearance distinction of particular objects in natural images due to intensity variations. To handle this, local ternary pattern introduced for texture classification. LTP has small pixel value variations as compared to LBP. LBP, LDP and LTP capture the feature information based on the distribution of edges which are coded using only two directions.

Q. Local Mesh Ternary Patterns (LMeTerP)

The standard local binary patterns and local ternary patterns (LTP) encode the gray scale relationship between the center pixel and its surrounding neighbors in two dimensional local region of an image. The former descriptors encodes the gray scale relationship among the neighbors for a given center pixel with three selected directions of mess patterns which are generated from 2D image and later descriptor encodes the spatial relation between any pair of neighbors in a local region along the given directions (i.e. 0°, 45°, 90° and 135°) for a given center pixel in an image [33]. In contrast to LBP, LQEP method provides the connection between any pair of neighbors in a local region for a given referenced pixel in an image and LMeP. This method provides the connection between the surrounding neighbors for a given referenced pixel in an image. LTP and LMeP motivated to propose the LMeTerP for biomedical image indexing and retrieval. In local mesh ternary patterns, the idea of local patterns (the LBP, the LTP and the LMeP) has been adopted to define LMeTerP to extend the standard LTP to LMeTerP [34]. The three local mesh pattern images at $j = 1, 2, 3$ using convolution operations from a given image are generated. This mesh ternary code is converted into two binary codes (upper LTP code and lower

LTP code) at different thresholds using the concept of LTP given. Also, by multiplying with the binomial weights to each LTP coding, the unique LMeTerP values (decimal values) for a particular selected mesh pattern (3×3) image for characterization of spatial structure of the local pattern are defined.

R. Local Extrema Peak Valley Pattern (LEPVP)

This method applies two-level discrete wavelet transform (DWT) on the image where it decomposes the image into high-resolution and low-resolution sub-images. Thereafter, it collects a three-valued code for each of the seven sub-images which is further split into two binary patterns-local extrema peak pattern (LEPP) and local extrema valley pattern (LEVP). Thus, this method uses local directional information to classify images. Intensity of each pixel is compared to that of a central pixel using $Zi = I_i - I_c$. The LEPP feature vector is obtained from LEPVP by replacing 1 by 0 and 2 by 1 and retaining 0. LEVP feature vector is obtained by replacing 2 by 0 and retaining 0 and 1. LEPVP method was introduced in [35] for image retrieval in large databases.

S. Local Neighborhood Intensity Patterns (LNIP)

The local patterns including LBP, concentrates mainly on the sign information and thus ignores the magnitude. The magnitude information which plays an auxiliary role to supply complementary information of texture descriptor is integrated in this approach by considering the mean of absolute deviation about each pixel from its adjacent neighbors. Taking this into account a new texture descriptor, named as local neighborhood intensity pattern was developed [36]. LNIP is an extension of popular LBP. It considers a radius of unit distance since closest neighboring pixels holds more discriminating information for texture descriptors. That is it considers relative intensity difference between a particular pixel and the center pixel by considering its adjacent neighbors and generate a sign and a magnitude pattern. Sign pattern and magnitude pattern are concatenated into a single feature descriptor to generate a more effective feature descriptor called LNIP [36].

T. Entropy Based Local Binary Pattern (ELBP)

Cloud Computing (CC) is a widely used technology that challenges exist in the form of security threats. There are a variety of services that are offered by cloud. These include Software as a Service (SaaS), Infrastructure as a Service (IaaS) and Platform as a Service (PaaS). Storage is one of the key service offerings under IaaS. To provide a secure digital platform for users to work with, the research work propose a novel security architecture for secured storage in cloud that provides a robust authentication by employing multiple biometric modalities from users and allow/deny access accordingly [37]. The crux of better authentication relies on the way the features are extracted from multiple biometric sensors and matched with registered users. For this purpose, a novel feature extraction technique called entropy based local binary pattern is applied. ELBP is a new texture-based feature extraction technique proposed to describe the entropy information into local binary pattern histogram in one-dimensional space. ELBP needs no quantization. Biometric images exhibit higher uniqueness and hence incorporating entropy values into local regions add higher information content to these images, thus leading to better feature extraction.

U. Circular Derivative Local Binary Pattern

A novel feature extraction technique used for facial expression recognition (FER) is called circular derivative local binary pattern (CDLBP). Motivated by uniform local binary patterns (u LBPs) which exhibits high discriminative potential at a reduced data dimension of the original LBP feature vector, CD-LBP feature descriptors are extracted as a result of binary derivatives of the circular binary patterns formed by LBPs [38]. Seven datasets consisting of CD-LBP feature vectors are derived from the Japanese female facial expression (JAFFE) database. Then these fed individually in a K-nearest neighbor classifier and evaluated with respect to their respective recognition rate and feature vector size. The experimental results demonstrate the relevance of the proposed feature description especially when performance metrics such as recognition accuracy and running time are considered.

V. Local Directional Peak Valley Binary Pattern

In LBP the relationship with only neighboring pixels in a particular radius are considered. But this method takes into account relationship of a pixel with its neighbor's methods for texture analysis such as LBP take into account only the eight closest neighbors of a central pixel as they provide more related information. This method supplements this information with the information from other surrounding pixels [39]. This is performed by computing peak (LDPBP) and valley (LDVBP) pattern values from the LBP value of each pixel instead of its pixel intensity. LBP calculations allocate a value to each pixel by comparing its pixel intensity with that of its neighbors. Further calculations are done by directly comparing LBP value of each pixel with those of its surrounding neighbors. Many content-based image retrieval (CBIR) methods are being developed to store more and more information about images in shorter feature vectors and to improve image retrieval rate. Two-step approach to CBIR has been developed. The first step generates an image mask from local binary pattern (LBP). This LBP mask is then utilized to draw comparison between the center pixel and the eight surrounding pixels. The second step involves drawing the peak and valley patterns of local directional binary pattern for each image which is then combined with the color histogram to retrieve similar images. Existing methods suffer from lower average image retrieval accuracy even with larger feature vectors [39]. The proposed method overcomes such problems through shorter feature vectors that can store more information about the image.

IV. CONCLUSIONS

There are many techniques available to analyze the texture on different image datasets. LBP is much efficient, easy to understand and implement technique for feature extraction and description of texture image. Many researchers implemented LBP and its variants for texture, facial, clinical analysis in more important daily life applications. There are many different forms of LBP patterns which are suitable for different application in biomedical, medical, biomedical engineering and other engineering fields. The LBPs variants are improved methods of LBP on different applications. The different datasets are used for implementations of these methods. To select a good descriptor to exploit textures in various fields of image processing, feature measures should be capable to detect different texture properties and computational complexity to make the algorithm realistic in technical use. It is concluded that the local binary pattern and its different extended variants provides good and efficient valuable results according to the need of that specific application.

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