A REVIEW OF ADVANCEMENTS IN LOCAL BINARY PATTERN TECHNIQUES IN IMAGE PROCESSING

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Abstract : . Image classification, image segmentation, pattern recognition, and image retrieval are based on feature extraction. Texture is the characteristic of a set of pixels that form an image, which is applied in many images as an important feature[1]. Analyzing texture helps detect important portions of the image. LBP is an efficient operator to recognize the pixels in the image. This paper provides a review on LBP and its variations. The aim of this review is to illustrate effectiveness of LBP and its variants in the field of image processing. LBP effectively preserves the essential visual elements of an image, as it is invariant to changes in light.

***IndexTerms* – Texture,Pattern,Threshold,Feature Extraction.**

I. INTRODUCTION

In the area of image processing and computer vision, texture indicates the replica of basic texture elements, which are referred to as texels. Texels consists of multiple pixels that are either placed randomly in a periodic manner. An image texture can be coarse, fine, smooth, granulated, rippled, regular, irregular or linear. Generally, texture reflects neighbor-surrounding points in the same way that a color reflects a point value . Scale is also one of the significant factor associated with texture, and a variant scale produces variant textures, even if the textures were equivalent [3]. A single image contains multiple levels of different textures that are located on different scales. One of the most common texture descriptors is the Local Binary Pattern (LBP), such descriptor is utilizing the structural and statistical features of the image in order to identify local characteristics. The literature showed great progress in the field of image feature extraction by using the LBP. LBP has encountered a variety of challenging issues such as the rotation, uniformity and others. Therefore, researchers have contributed toward proposing adaptations, modification and alteration of the LBP descriptor. This paper aims to review these modifications of LBP.

II. LOCAL BINARY PATTERNS

The Local Binary Pattern (LBP) is a methodology that extricates nearby elements from a picture by computing the distinction in neighborhood power between the worth of the focal pixel and the encompassing pixels (adjoining pixels). Next, it will summarize the patterns and explain the whole picture. Fig 1 describes the LBP process of selecting a block,finding its threshold, converting the binary values to decimal and generating historgram[2].

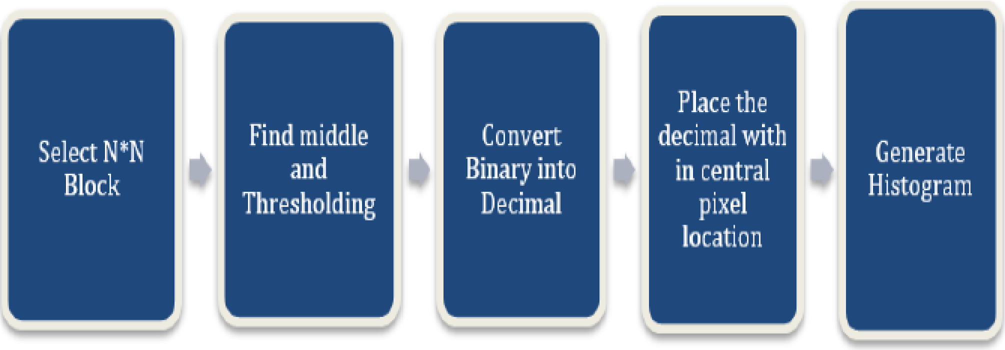

Fig:1 Block Diagram of LBP

Ojala et al. [4] used it as a potential grayscale invariant texture descriptor . A LBP operator performs both structural as well as statistical analysis of the texture of the images. The texture is represented using micro primitives according to the statistical placement rules. The LBP represents the eight surrounding pixels in binary code on a pixel basis. It summarizes all codes with the help of a histogram, to facilitate the extraction of a texture feature. Therefore, for a 3 × 3 neighboring, a 256- texture pattern is produced. A 3 × 3 grayscale block of pixels matrix B is shown, where the center is located at (0,0). LBP subtracts the coordinates from each of its neighbor as indicated.

$$B = \begin{pmatrix} g_8 & g_1 & g_2 \\ g_7 & g_{(0,0)} & g_3 \\ g_6 & g_5 & g_4 \end{pmatrix} \quad (1)$$

This matrix shows a 3 × 3 grayscale block of pixels, in which the center is located at (0,0). In this manner, LBP will subtract the coordinate from each neighbor as follows:

$$LBP1 = \begin{pmatrix} (g_8 - g_{center}) & (g_1 - g_{center}) & (g_2 - g_{center}) \\ (g_7 - g_{center}) & g_{center} & (g_3 - g_{center}) \\ (g_6 - g_{center}) & (g_5 - g_{center}) & (g_4 - g_{center}) \end{pmatrix} \quad (2)$$

To generate the binary code, the following equation should be considered:

$$LBP2 = \begin{pmatrix} s(g_8 - g_{center}) & s(g_1 - g_{center}) & s(g_2 - g_{center}) \\ s(g_7 - g_{center}) & g_{center} & s(g_3 - g_{center}) \\ s(g_6 - g_{center}) & s(g_5 - g_{center}) & s(g_4 - g_{center}) \end{pmatrix} \quad (3)$$

$$s(x) = \begin{cases} 1 & if\ x \geq 0 \\ 0 & if\ x < 0 \end{cases}$$

Consequentially, an eight-bit binary pattern will be encoded as follows:

$$LBP = \sum_{a=0}^{8} s_{(g_a - g_c)} 2^p \quad (4)$$

The 256-bit pattern that is produced by (3) is used to construct a histogram, to facilitate the process of description of textures. A Texture is an important characteristic of different types of images which is involved in numerous images Different local texture descriptors have been proposed, the local binary pattern is most commonly used one. The local binary pattern (LBP) was originally presented as a texture descriptor [5]. The LBP has been utilized in several domains of computer vision, such as face recognition and facial expression recognition, to model motion and actions. Multiple modifications have been conducted on the original LBP as per need to fit different kinds of tasks. The LBP is quite significant in texture analysis, the applications range from 2D to 3D textures. The LBP is a method that may be considered for both the statistical and structural models of texture analysis. The success factor for the LBP is its accurate monotonic grayscale changes, such as illumination variations. The LBP has another advantage i.e. its simple computations-which makes its use significant in the area of real-time analysis of images.
The structure of a texture has perspectives: the pattern and the strength. The annotation of pixels o by a specific threshold and comparison of the neighboring pixels with the center will result as a binary number. This value will be used as a texture descriptor.

Example

6	5	2
7	6	1
9	8	7

Threshold

1	0	0
1		0
1	1	1

Weights

1	2	4
128		8
64	32	16

The first table containing a 3×3 pixel, represents an image portion. The LBP compare all surrounding pixels against the center. The comparison attempts to recognize the smaller and greater values. The pixels that have greater values than the center will be encoded as 1, and the pixels with smaller values than the center will be encoded as 0, which is shown in the second table (i.e. threshold). The extracted pattern '10001111' will be utilized as a texture feature for learning purposes. The third table provides an assumption by assigning weights to all pixels (which are powers of 2).
The LBP is computed by summing all corresponding pixels in the second table as follows:
LBP =1+128+64+32+16 = 241
C, is the contrast measure, computed by summing all the corresponding pixels of '1' divided by their number and then subtracting them from the corresponding pixels of '0' divided by their number as follows:

$$C = \frac{6+7+9+8+7}{5} - \frac{5+2+1}{3} = 4.7$$

Note that if all pixels have the same values of '1' or '0', the results of C will be zero. The C and 2D distributions of the LBP codes are used as feature vectors in texture analysis, such as recognition.

Advantages of Local Binary Pattern (LBP)

1. **Simple and Efficient:** LBP is computationally efficient, making it suitable for real-time applications such as face recognition, texture classification, and industrial inspection.
2. **Robust to Illumination Changes:** Since LBP works with relative pixel intensity differences, it is less sensitive to variations in lighting conditions.
3. **Local Texture Representation:** Captures fine texture details, making it effective in tasks like medical imaging and biometrics.
4. **Easy to Combine with Other Descriptors:** LBP can be integrated with histogram-based and deep-learning methods to enhance feature extraction.

III. MODIFICATIONS TO LBP AND THIER ADVANTAGES

Uniform local binary pattern

Ojala et al. [6] have identified some frequent patterns, such as edges, curves and spots. These patterns are represented by the transition from ‘1’ to ‘0’ in the matrix as follows:

1	0	0
1		0
1	1	1

Based on these patterns, uniform local binary patterns (U-LBP) were introduced. The U-LBP minimizes the number of patterns, and reduces the length of the feature vector. The binary patterns have the majority of the frequency which is the most significant property of a texture. These patterns can be determined using a uniformity measure to identify the spatial transition. Figure 1 shows an image, the left side of the image shows the non-uniform changes and the right side shows the uniform changes. The uniformity pattern is computed as below:

$$LBP^{riu2}_{p,r} = \begin{cases} \sum_{p=0}^{p-1} s(g_p - g_c) & if \quad U(LBP_{P,R}) \leq 2 \\ P+1 & otherwise \end{cases} \quad (5)$$

Where,

$$U(LBP_{p,r}) = \left| s(g_p - g_c) - s(g_0 - g_c) \right| + \sum_{p=1}^{p-1} \left| s(g_p - g_c) - s(g_0 - g_c) \right|$$

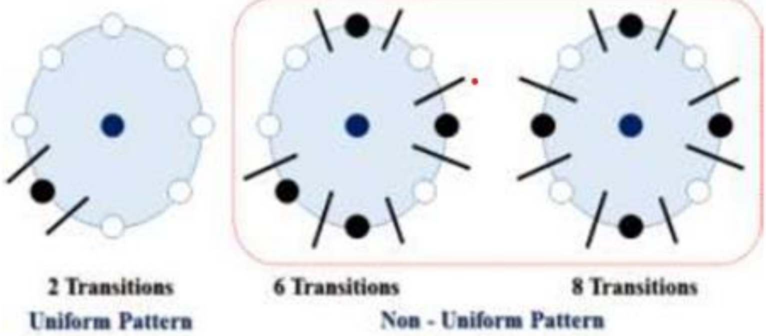

Fig 2:Uniform and Non Uniform Patterns

The uniform local binary pattern, diminishes the dimensionality of the highlighted feature vector and examine its rotation invariant. The hypothesis is that some of the binary patterns in texture images occur more commonly than other patterns. LBP are said to be uniform in the event of design containing double i.e. at most two—0-1 or 1-0—transitions. The uniform local patterns and length of the feature vector used for a single cell is reduced from 256 to 59.

Advantages of Uniform LBP (ULBP)

1. **Feature Dimensionality Reduction:** ULBP focuses only on uniform patterns (which have at most two bitwise transitions), significantly reducing the number of possible patterns and improving computational efficiency.

2. **Retains Essential Texture Information:** Most natural textures are represented by uniform patterns, making ULBP an effective feature extractor while discarding less relevant data.
3. **Improves Classification Accuracy:** ULBP enhances performance in applications like face recognition, fingerprint analysis, and medical image processing.
4. **More Robust to Noise:** Eliminating non-uniform patterns reduces the sensitivity of the LBP descriptor to noise, making it more reliable in real-world applications.

Rotation invariant local binary pattern

The rotation of an image is performed to change the values of neighbors that surround the centers. The rotation invariant LBP has the ability to overcomes this issue by shifting the binary structure using the following equation:

$$LBP_{p,r}^{ri} = \min\left\{ROR\left(LBP_{p,r}, i\right) \middle| i = 0, 1, \ldots, P-1\right\}$$

The ROR (x,i) performs a circular bitwise right shift on the P bit number. Figure 2 shows the rotation, to demonstrate the change in the values of the neighbors . From the fig 2, it is evident that The pattern of the image before the rotation is different from the pattern after rotation. By using the rotation invariant LBP, the patterns can be identical.

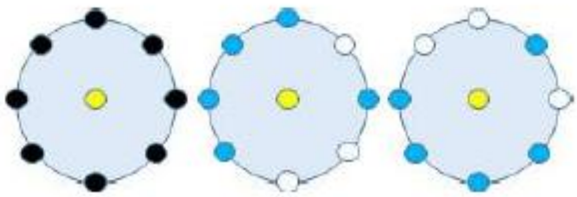

Fig:3 The patterns before and after Rotation

Advantages of Rotation Invariant LBP (RILBP)

1. **Eliminates Orientation Dependency:** RILBP makes the feature extraction process invariant to object orientation, which is useful in applications like remote sensing, defect detection, and biomedical imaging.
2. **Enhances Texture Classification Performance:** By considering all possible rotations of an LBP pattern and selecting the minimum binary value, RILBP improves classification accuracy in datasets with varying orientations.
3. **Effective in Real-World Scenarios:** Objects in natural environments often appear in different orientations; RILBP ensures reliable feature extraction regardless of these changes.
4. **Preserves Discriminative Power:** RILBP retains enough texture information for distinguishing different patterns.

Entropy based Local Binary Pattern (ELBP)

Entropy based LBP (ELBP) is proposed to improve the performance of feature extraction technique. The ELBP computes the information content of each neighbourhood pixel, to calculate the entropy contribution, which is used as an adaptive weight to estimate the information gained from each neighbouring pixel.

The entropy-based rotation invariant method is an extension to the conventional LBPV approach. This approach, brings out high information content present in biometric images'. The images under consideration are biometric images from which features are extracted based on texture. ELBP feature extraction is applied to biometric images Consideration of non-uniform patterns for biometric images add more significance in extraction features as biometric images are highly unique and differ greatly from one user to another.

The matching more robust against local spatial structural changes is based on Entropy of the local absolute difference. Entropy is defined as a measure of the expected information content or uncertainty of a probability distribution. The lower probabilities result in higher information gain. Let Xi denote a pixel and pi denote the probability of occurrence of that pixel Xi. Let n be the number of such pixels in a given image. Hence, the pixels X1, …, Xn with p1, …, pn as probabilities, add up to 1. The probability of occurrence and information content are inversely proportional. Thus, entropy h, a measure of information is a decreasing function of probability pi. Claude Shannon proposed a log function h(pi) to define information and is given by the following equation.

$$h(g_{p_i}) = \log_2 \frac{1}{P(g_{p_i})}$$

where (gpi) deotes the probability of sampling pixel. It is a decreasing function from infinity to 0. The value of P(gpi) ranges between 0 and 1. The lower the probability of a pixel to exist, the higher will be the amount of information. This is more relevant in a biometric image, since lower the probability, more unique the extracted feature is. From these n information values h(gpi), the expected information content entropy H, is formulated by measuring the information value and associated probabilities.

$$H = -\sum_{i=1}^{n} P\left(g_{p_i}\right) \log_2 P\left(g_{p_i}\right)$$

Given a discrete random variable R with probabilities P=(P1,...,Pn), the Shannon entropy can be defined as

$$H(g_p) = -k\sum_{i=1}^{n} P\left(g_{p_i}\right) ln\, P\left(g_{p_i}\right)$$

Advantages of Entropy-Based LBP (ELBP)

1. **Enhances Feature Discrimination:** ELBP captures the complexity and randomness of texture patterns, making it highly effective for distinguishing fine-grained textures.
2. **Better Representation of High-Variation Images:** ELBP performs well in applications where textures have significant variations, such as medical imaging, satellite image analysis, and microscopic image classification.
3. **Adaptive to Local Texture Variations:** Unlike standard LBP, which treats all patterns equally, ELBP gives more importance to regions with higher entropy, ensuring better feature extraction in detailed textures.

IV. CONCLUSION

Each LBP variant enhances texture analysis by addressing specific limitations. RILBP provides robustness to rotation, ULBP reduces computational complexity while maintaining key texture features, and ELBP improves feature discrimination in high-variation textures. Selecting the appropriate variant depends on the application's need for efficiency, robustness, and classification accuracy.This paper provided a review on LBP as a texture descriptor along with its modifications. Most of the proposed modifications of LBP were intended to solve specific problems such as structural and averaging information. The LBP and other descriptors can be combined to obtain better results.

V. REFERENCES

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