CHAPTER 6

GLOBAL AND LOCAL LINEAR SIGNIFICANT BINARY PATTERN FOR A ROBUST AND ROTATIONAL INVARIANT CLASSIFICATION

6.1 INTRODUCTION

For a precise texture classification and analysis, local or global features are extracted in the literature. By extracting the local features, the global information will be missing and vice versa. To overcome this, the present study developed a model with local and global texture features. Rotation invariant local or global features play an important role in texture classification and analysis. LBP is a widely used tool for texture classification based on local features i.e., LBP looses global spatial information completely. Moreover LBP does not provide greater amount of discriminant information of the local structure and it has a various other disadvantages. To represent the missing local information effectively in the LBP, the present study derived a new Significant Local LBP (SLLBP). The SLLBP uses only two components of Completed LBP (CLBP), i.e., S-LBP and M-LBP. The main disadvantage of CLBP is, that it compares the centre pixel value with its neighbors to derive S-LBP and M-LBP. The basic drawback of this comparison is that it is very sensitive to noise. And a major contrast between the central pixel and its surroundings are easily resulted by the slight fluctuations above or below the value of the Centre Pixel (CP) and its surroundings. To overcome this problem, the proposed method used NICK based thresholding method on LBP value to derive Significant Sign LBP (SS-LBP) and Significant Magnitude LBP (SM-LBP).
This overcomes the problem related to noise and contrast. By using the OR operation between SS-LBP and SM-LBP, the present study derived SLLBP which holds all significant local information. One of the disadvantages of SLLBP is it has no global features. After an extensive study, the present work understood that for a precise, accurate and better texture analysis and classification, one needs both local and global, rotationally invariant features of the texture. For this, the present study derived SGLLBP which provides globally rotation invariant features on the SLLBP by using variance. SGLLBP provides accurate and robust representation of textures because SGLLBP takes care of spatial structure (by using patterns of SLLBP) and the contrast (by using variance). Spatial features vary with rotation whereas contrast does not.

6.2 PROPOSED SGLLBP

The proposed SGLLBP scheme is given in the form of block diagram as shown in Fig.6.1.

![Fig.6.1: Proposed significant global local LBP (SGLLBP) representation.](image)

The proposed SGLLBP consists of the following steps:

1. Color to gray conversion using RGB or HSV color space.
2. Conversion of gray level image to SS-LBP using NICK threshold.
3. Conversion of gray level image of step-1 to significant magnitude LBP (SM-LBP) using NICK based threshold.


5. Disjunction operation between SS-LBP of step-2 and BLBP of step 4 gives SLLBP.

6. Apply variance on SLLBP to get SGLLBP.

The conventional LBP operator has some disadvantages and limitations:

1. The histograms produced by LBP are wide and sensitive to image rotation.

2. The LBP operator fails to properly detecting large-scale textural structures due to their small spatial support.

3. Only the sign of differences of neighboring pixels is utilized in LBP, by which it may lose significant local textural information.

4. LBP is very sensitive to noise. A major contrast between the central pixel and its surroundings is easily resulted by the slight fluctuations above or below the value of the central pixel with its neighbors.

To address the above limitations, a number of rotation invariant texture classification methods were been proposed [29, 55, 73, 83, 99, 111, 124] including LBP. They extract rotation invariant texture features from a local region, but sometimes fail in extracting significant texture information.

Based on the above drawbacks, the present study proposes SLLBP. The SLLBP can analyze texture images both globally and locally.
6.2.1 Derivation of SLLBP

The SLLBP is based on completed LBP (CLBP). The CLBP contains three components called CLBP-M, CLBP-S and CLBP-C. The local region is represented by CLMP-M. The CLBP-M is formed by taking the difference between centre pixel and neighborhood pixel. The CLBP-S represents the sign values (+1, -1) for CLMP-M. The CLBP-C represents the global information i.e., instead of centre pixel value a global threshold is used. After an indepth study of CLBP, the present study found that just like LBP, the CLBP-M and CLBP-S produces noise and other contrast related problems because of local comparison i.e., centre pixel with neighboring pixels. To overcome this, the present study used Nick based thresholding.

The NICK method is an improvement on Niblack’s method developed by Khurshid et al. [57, 80]. Its aim is to solve the problem of black noise and the low contrast problem by shifting the threshold value downward. The threshold value is calculated by using Eqn.(6.1).

\[ T_n = \mu + k \sqrt{\frac{\sum P_i^2 - \mu^2}{N}} \]  

where k is a factor in the range [-0.2,-0.1], P is the pixel value of the gray scale levels in the image, and N is the total number of pixels in the image. The NICK method of LBP overcomes black noise and low contrast problems of CLBP. The other drawbacks of LBP, CLBP, CCR, ILBP, etc., is sometimes two or more different blocks which may represent same LBP code as shown in Fig.6.2. From Fig.6.2 (a) and (b), the LBP, CLBP, CCR, ILBP, etc., yields same binary codes because they simply compare the centre pixel value with the surrounding neighbors. This may result problems related to noise and contrast. To overcome this, the proposed
SLLBP used NICK based threshold as shown in Fig.6.3. For the same different blocks of image of Fig.6.2, the SLLBP yield two completely different SS-LBP and SM-LBP as shown in Fig.6.3 and 6.4. The SS-LBP represents sign in the form of binary code i.e., positive values as +1 and negative/zero values as 0. The disjunction operation between SS-LBP and BLBP of SM-LBP produces SLLBP.

Fig.6.2: (a)&(b) are two subimages (c) Similar LBP for two different regions of Fig.6.1(a)&(b).

Fig.6.3: Illustration of SLLBP transform. (a)Fig.6.2(a) subimage (b) SS-LBP (c) SM-LBP (d) Binary LBP of SM-LBP (e) disjunction operation on SS-LBP and BLBP results SLLBP.
Fig. 6.4: Illustration of SLLBP transform. (a) Fig. 6.2(b) subimage (b) SS-LBP (c) SM-LBP (d) Binary LBP of SM-LBP (e) disjunction operation on SS-LBP and BLBP results SLLBP.

6.2.2 Derivation of SGLLBP

Ojala et al. [83] proposed a joint histogram of two complementary features namely LBP and variance for a rotation invariant texture classification. The disadvantages of this scheme are (1) it is sensitive to noise due to the threshold applied (2) the continuous value of variance needs a quantization step for generating the histogram (3) it requires a large number of training samples for constructing a good quantization. To overcome these disadvantages, the present study proposed Significant Global LBP (SGLBP), which provides globally rotation invariant features on SLLBP using rotation invariance histogram. The SGLBP basically characterizes the contrast information on the histogram. Many texture classification and analysis methods [55, 73, 83, 124] including LBP, CLBP, CCR, ILBP, etc., extract, rotation invariant texture features but fail in classifying the following different pattern of textures as shown in Fig. 6.5.
Fig. 6.5: (a,b) the LBP codes of two texture images, each of which is composed of two LBP micro patterns. By using LBP rotation invariant LBP micro pattern in (c), the two different images will be misclassified as the same class.

The Fig. 6.5 (a) and (b) show two different textures with different micro patterns. These two images clearly show different texture information. The rotation invariant LBP of these two images misclassifies them as the same class as shown in Fig. 6.5(c). This is due to losing global information and ignoring significant local features. To address this and to achieve robust, accurate and precise rotation invariant texture classification, the present study applied LBP-variance on SLLBP, to obtain SGLLBP. The SGLLBP represents both spatial structure and contrast.

To represent these two complementary features i.e., spatial structure and contrast, as a joint histogram for rotation invariant classification, one needs a quantization step. This quantization process is one of the drawbacks if one wants to consider the above two features. The proposed SGLLBP also requires quantization step to represent both spatial structures and contrast as a joint histogram. Instead of computing the joint histogram of LBP spatial structures and contrast represented by VAR globally, the proposed SGLLBP computes the VAR from the significant local LBP and accumulates it into the LBP bin. This further reduces greatly the requirement for dependency on a large number of training
samples. The SGLLPB histogram is computed using Eqs. (6.2) & (6.3) respectively.

\[
SGLLPB(k) = \sum_{i=1}^{M} \sum_{j=1}^{N} W(SLLBP_{(P,R)}(i,j), k), \quad k \in [0, K] \tag{6.2}
\]

\[
W(SLLBP_{(P,R)}(i,j), k) = \begin{cases} 
\text{VAR}_{P,R}(i,j), & \text{SLLBP}_{(P,R)}(i,j) = k \\
0, & \text{otherwise}
\end{cases} \tag{6.3}
\]

where \(\text{VAR}_{P,R}(k)\) represents variance of 3×3 neighborhood. The Eqs. (6.3) & (6.4) guarantee that the proposed SGLLPB is training free and it doesn’t need quantization. The joint histogram algorithm of SGLLPB is given below.

Algorithm 6.1: Joint histogram routine of SGLLPB (VarLPB on SLLBP).

begin

Step 1: Compute the original SGLLPB histogram:

\[h = \{h_1, h_2, \cdots, h_{256}\} \tag{6.4}\]

Step 2: Remove the first and the last bins of the histogram as they represent all-black and all-white constant patterns:

\[h' = \{h_2, h_3, \cdots, h_{255}\} \tag{6.5}\]

Step 3: Rearrange the resulting SGLLPB histogram into blocks of bins so that each block refers to rotationally equivalent patterns:

\[h' = \{h_1, \cdots, h_M\} \tag{6.6}\]

where, \(h_i = \{h_{i1}, \cdots, h_{iN}\}\) and \(M = 34\). Imagine that each group of rotation invariant patterns is formed by a basic pattern and all its rotated versions.

Step 4: The feature vector \(H\) of the rotation invariant texture is obtained by concatenating the histograms of each layer:

\[H = [H_1, H_2, H_3, \ldots, H_M].\]
Step 5: Add to the above feature vector, the first and last elements of the histogram which were previously removed in step (2). The resulting feature space is denoted by SGLLBP histogram.

Step 6: The obtained SGLLBP is clustering of all the patterns that are rotated version of the same pattern. This operation reduces the number of possible patterns, and improves the performance of SGLLBP by exploiting the local contrast information.

To satisfy the circular shift property, the proposed method orders each group of bins. This refers to a group of rotation invariant patterns in such a way that if the \( h_{i1} \) bin refers to the basic pattern then the \( h_{i2} \) bin refers to the pattern obtained through a single rotation of \( 45^0 \) from the basic pattern, and so on. As the texture rotates by \( 45^0 \), the corresponding histogram bins undergoes a circular shift by one position. In general, each group is composed of eight different rotationally equivalent patterns (therefore \( N = 8 \)). In some cases, the number of different patterns for each group is less than eight. This occurs when a rotated version of a pattern coincides with the unrotated version.

6.3 EXPERIMENTAL RESULTS

To evaluate the effectiveness of the proposed method, experiments are conducted on two different datasets. The first dataset i.e., Dataset-1 is composed of 45 texture classes (one image for each class) from the OuTex library [86] as shown in Fig.6.6. The size of the original images is \( 746 \times 538 \) pixels. As the texture surface rotates, only the central part of the image captures the same portion of the surface. For this reason, the central part of the rotated images is retained which is calculated by \( \min(W,H)/\sqrt{2} \).
where \( W \) and \( H \) are the width and height of the original images. The resultant images are of size \( 380 \times 380 \) pixels. The second dataset, i.e., Dataset-2 is composed of 12 granite texture classes [7]. The overall dataset is composed of 48 images, 4 for each class as shown in Fig.6.7. The size of the original images is \( 1024 \times 768 \) pixels. The central part of the rotated images is calculated and the resultant images are of size \( 544 \times 544 \) pixels.

To assess robustness against rotation, images are rotated at angles: \( 0^\circ, 5^\circ, 10^\circ, 15^\circ, 30^\circ, 45^\circ, 60^\circ, 75^\circ \) and \( 90^\circ \). Bilinear and Bicubic interpolation are the two approaches used to rotate the images. The function \texttt{imrotate} of the Matlab package is used to perform these interpolations. The present study accessed the robustness and preciseness against classification even with small angle difference because this may cause ambiguity to a gray level pattern. Fig.6.8 gives an example of the changes which may suffer a gray-scale pattern when rotated by \( 5^\circ \) through bilinear interpolation. As observed, even a small rotation angle can induce changes in the corresponding local binary pattern, which are likely to degrade the classification accuracy.

The classification experiments are based on the nearest neighbor rule [28] with the \( L_1 \) norm, also called Manhattan distance. The texture samples are divided randomly into two non-overlapping groups (training set and validation set) of half the samples each. In order to assess the robustness against rotation, the training set is always composed of textures picked from the \( 0^\circ \) group, while the validation set is composed of rotated versions of textures taken from the \( \theta^\circ \) group where \( \theta \in \{0^\circ, 5^\circ, 10^\circ, 15^\circ, 30^\circ, 45^\circ, 60^\circ, 75^\circ, 90^\circ\} \).
Fig. 6.6: Dataset-1: 45 texture classes (one image for each class) from OuTex. Canvas{005, 021}; Carpet{005}; Granite{001, 003, 004, 005, 006, 007, 008, 009, 010}; Paper{006}; Plastic{001, 002, 003, 004, 005, 009, 016, 017, 018, 019, 020, 021, 022, 023, 024, 025, 026, 027, 028, 029, 030, 031, 032, 033, 034, 035, 036, 038, 040, 041}; Wood{006, 008}. 
Fig. 6.7: Dataset-2: The dataset of granite textures used in the experiments (unrotated images). From the top: Acquamarina, Azul Capixaba, Bianco Cristal, Bianco Sardo, Rosa Beta, Azul Platino, Giallo Ornamentale, Giallo Napoletano, Giallo Santa Cecilia, Giallo Veneziano, Rosa Porriño A, Rosa Porriño B.
Fig.6.8: An example of the effect of 5° rotations through bilinear interpolation on the texture structure. Even a small rotation angle may induce changes in the LBP code of a grayscale pattern.

The percentage of correct classification is the ratio between the number of textures of the validation set correctly classified and the total number of textures of the validation set. For each angle, the estimated percentage of correct classification is averaged over 100 different random partitions of data into training and validation set in order to make the estimation stable.

The experiments are conducted for the proposed SGLLBP versus LBP_{3x3} of [83], LBP_{6,1}^{ri} of [83], CLBP_{6,1}^{ri} of [138], CCR_{6,1}^{ri} of [33] using bilinear and bicubic interpolations and the results are summarized in the Tables 6.1 and 6.2. From the Tables 6.1 and 6.2, it is clearly evident that the classification results achieved by the rotationally invariant descriptor (ri) at 90° synthetically rotated data closely matched the classification results obtained at 0°. These results are motivated by the fact that no interpolation is required for orthogonal rotations (90, 180 and 270 degrees), since the image rotation for these orientations involve one-to-one pixel mapping. From the Tables 6.1 and 6.2, it is clearly evident that the
proposed SGLLBP is superior to the existing methods in classification of textures.

Table 6.1: Classification results with the Dataset-1 from OuTex database

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<th>$A_3^0$</th>
<th>$A_{10}^0$</th>
<th>$A_{15}^0$</th>
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<th>$A_{45}^0$</th>
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Table 6.2: Classification results with the Dataset-2 from Granite textures

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**SUMMARY**

By extracting the local features the global information will be missing and vice versa. To overcome this, the present study developed a model with local and global texture features for texture classification and analysis. The basic drawback of LBP is that it compares the central pixel value with the neighboring values to evaluate the LBP pattern. This comparison is very sensitive to noise and fail in properly detecting large-
scale textural structures due to their small spatial support. Further, a major contrast between the central pixel and its surroundings are easily resulted by the slight fluctuations above or below the value of the CP and its surroundings. To overcome this, the present thesis derived significant LBP using NICK based threshold. One of the disadvantages of the proposed SLLBP is it has no global features though it has significant local features without noise and contrast related problems. For a precise, accurate, better texture analysis and classification with both local and global, rotationally invariant features of the texture, the present study derived SGLLBP which provides globally rotation invariant features on the SLLBP by using variance.

The proposed SGLLBP provides accurate and robust representation of textures, because SGLLBP takes care of spatial structure (by using patterns of SLLBP) and the contrast (by using variance). Many texture classification and analysis methods [55, 73, 83, 124] including LBP, CLBP, CCR, ILBP, etc., extract rotation invariant texture features but fails in classifying many different pattern of textures. The Fig.6.5(a) and (b) shows two different textures with different micro patterns. These two images show clearly different texture information. The rotation invariant LBP of these two images misclassifies them as the same class as shown in Fig.6.5(c). This is due to loosing of global information and ignoring the significant local features. To address this and to achieve robust, accurate and precise rotation invariant texture classification, the present study applied LBP-variance on SLLBP to obtain SGLLBP. The SGLLBP represents both spatial structure and contrast.
Ojala et al. [83] proposed a joint histogram of two complementary features namely LBP and variance for a rotation invariant texture classification. The disadvantage of this scheme is (1) it is sensitive to noise due to the threshold applied (2) the continuous value of variance needs a quantization step for building the histogram (3) it requires a large number of training samples for constructing a good quantization. To overcome this, the present study proposed SGLLBP which provides globally rotation invariant features on SLLBP using rotation invariance histogram. The SGLLBP basically characterizes the contrast information on the histogram. The proposed SGLLBP also requires quantization step to represent both spatial structures and contrast as a joint histogram. Instead of computing the joint histogram of LBP spatial structures and contrast represented by VAR globally, the proposed SGLLBP computes the VAR from the significant local LBP and accumulates it into the LBP bin. This further reduces greatly the requirement for dependency on a large number of training samples very much.

The proposed SGLLBP is compared with LBP_{3×3} of [83], LBP_{ri} of [83], CLBP_{ri} of [138], CCR_{ri} of [33] using bilinear and bicubic interpolations and the results are summarized in the tables. From the Table 6.1 and Table 6.2, it is clearly evident that proposed SGLLBP is superior to the existing methods in classification of textures.