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AGLV: An Effective Texture Classification Method Based on Local Binary Pattern

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ABSTRACT
Local binary pattern (LBP) is local texture descriptor widely used in texture classification due to its computational simplicity. However, the LBP descriptor has some weakness such as very sensitive to image rotation, image noise and illumination. In addition to this, LBP consider only sign difference and ignores magnitude difference that reduces its discrimination ability. In order to overcome these weaknesses of original LBP, this research work proposed new texture classification method based on LBP called Average Gray Level Value (AGLV). To make AGLV method rotation invariant and illumination invariant image is divided into 3*3 regions and use average gray level value of each region to calculate Sign Difference, Magnitude Difference, Region Based Gray Level value, Min-Max value and β value features from image. All these features capture more detail texture information for rotation invariant and illumination invariant texture classification. The AGLV method use KNN and SVM classifier for texture classification. The performance of proposed AGLV method is tested using Brodatz, Kylberg and Kth-Tips database. The experiment result shows that, the proposed AGLV method is rotation invariant and illumination invariant. It achieves higher classification result as compare to original LBP method. The texture classification result achieved by AGLV method by using kylberg texture database is 98.00%, brodatz database 92.02% and using Kth-Tips database is 42.50%.
Keywords — Texture, Texture Classification, LBP, Average Gray Level Value, Rotation invariant, Illumination invariant.

I. INTRODUCTION

Texture is one of the basic important features that describe gray level changes in image. It play important role in classification of texture image. Texture classification can be defined as, assigning unknown image to one of the known class. It consists of two main steps. First step is extracting texture features from image and the second step is classification. It compare test image with all training images and give result as class name. Texture classification has wide range of application such as face recognition [1], image retrieval [2], fabric inspection [3], remote sensing [4], medical image analysis [5] and so on. If the poor and weak texture features used for texture classification then best classifier will fail to achieve good classification result. However, a common problem in texture classification is that, variation in image orientation and image illumination. It can affect the result of texture classification. Consequently, many researchers focused on developing powerful and efficient texture classification method that is rotation invariant and illumination invariant. Gaussian Markov Random Field [6], GLCM [7], Wavelet Transform [8], LBP [10] are some example of texture classification method developed by researcher. Among these methods we focused on Local Binary Pattern (LBP) because of its less computational complexity.

Before introducing LBP, Ojala et. al.[9] study the gray level difference between pair of gray level to generate histogram and used as texture descriptor of image. In [10] Ojala develop local texture descriptor work only on gray scale images called Local Binary Pattern (LBP). It uses only signed difference to generate eight bit binary pattern. LBP is efficient and popular texture descriptor due to its low computational complexity and ability to differentiate the macro structure of image such as edge, line and spots.

Local binary pattern has some limitations such as highly sensitive to image rotation, image noise and change in image illumination. Consequence of these limitations, LBP is not able to extract robust texture features from image. To overcome these limitations, researcher developed various texture descriptor based on LBP called LBP variants. LBP riu2[10], LBPriu2/VAR[10], DLBP[11], CLBP[12], MB-LBP[13], ALBP[14], MRELBP[15], AFLBP[16], CRLBP[17], FBLBP [18] are example of LBP variants.

In this paper, we try to solve the difficulties of original LBP method using proposed new texture descriptor called Average gray level value (AGLV) method. The AGLV method use average value of 3*3 regions of image. It is used to calculate sign difference and magnitude difference features. In addition to this, Region Based Gray Level value, Min-Max value and β value is calculated from each region of image. All these features are used as texture features for rotation invariant and illumination invariant texture classification. Experiment result shows that the AGLV method is rotation invariant and illumination invariant. It achieves higher classification result then original LBP method.

The rest of the paper is organized as follows: sections 2 briefly review on original LBP method. It also gives detail information of proposed AGLV method. The experiment results using standard texture databases are discussed in section 3. Finally, section 4 concludes the whole paper.

II. AVERAGE GRAY LEVEL VALUE

In this section, we briefly review on original LBP method and its limitations. To improve the performance of texture classification, this research work proposed new texture classification method based on LBP called Average Gray Level Value (AGLV) method. It has an ability to extract rotation invariant and illumination invariant texture features from image.

A. *Brief Review on Local Binary Pattern*

Local Binary Pattern introduced by ojala [10] extracts only local texture features from greyscale image. It use 3×3 neighbourhood structure and extract local texture features from each pixel of image. Figure 1 shows the concept of Local Binary Pattern. It performs thresholding operation between central pixel and its surrounding pixels (neighbouring pixels). Thresholding means comparison between central pixel value and its neighbouring pixel value. The result of comparison is set to binary 1 if the value of neighbouring pixel is greater than or equal to the value of central pixel. Otherwise, it is set to binary 0.

The eight bit binary number is generated shown in figure 1. Read this binary number in clockwise direction. The LBP code is obtained by converting binary number to decimal number. Then decimal number is used to label the central pixel of image region. After this, histogram of LBP label is computed over whole image and used as texture features of image. The LBP features of image are calculated by using following equations.

$$LBP = \sum_{i=1}^{n} s(Pi - Pc) \times 2^{i}$$

$$\text{where } S(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \qquad ------(1)$$

Where, the function $S(x)$ perform thresholding operation, Pc represent gray level value of the central pixel and Pi represent gray level value of neighbouring pixel (i=1, 2, ---, 8). Figure 1 shows Local Binary Pattern.

65	87	77
45	81	92
3	89	72

Sample Block

0	1	0
0		1
0	1	0

Thresholding

Binary Pattern=01010100

Fig. 1 Local Binary Pattern

The original LBP method has some limitations. These are:

- It is sensitive to image noise, image rotation and illumination.
- It uses 3*3 neighborhood system to extract local texture information from image. Little change to central pixel of image region can change binary pattern drastically.
- Texture information captured by original LBP method is limited due to use of only sign difference and ignores magnitude difference.

B. *Average Gray Level Value (AGLV) method*

Motivated from limitations of original LBP method, this research work proposed new texture classification method based on LBP called Average gray level value (AGLV) method. It explores different way to extract local texture features from image effectively. The AGLV method divides the image into 3*3 regions and performs thresholding operation on image called Sign Difference.

The AGLV method modifies the configuration of original LBP method. It not only uses average based Sign Difference but also use average based Magnitude Difference of neighbouring pixel. It can be defined as:

$$SD = \sum_{i=1}^{9} s(Pi - AVG) \times 2^{i}$$

$$\text{where } S(x) = \begin{cases} 1 & x \geq AVG \\ 0 & x < AVG \end{cases} \qquad ----(2)$$

$$MD = |AGV - Pi| + |Pi - AGV| \qquad ----(3)$$

$$AVG = \left(\sum_{i=1}^{9} Pi\right)/9$$

Where AVG is average intensity value of all pixel in 3*3 region and Pi (i=1, 2, 3, ------, 9) indicate the pixel of image region. SD represents Sign Difference and MD represents symmetric difference between pixel intensity value and average value of image region. All pixels in image are encoded by equation 2 and 3. In addition to this, the proposed method also extract Region Based Gray Level (RBGL), Min-Max value and β value of each 3*3 region of image to represent more detail texture information of image.

The RBGL and Min-Max value represent the gray level changes between different regions of image. All regions of given image is also encoded by region based gray level (RBGL) and Min-Max value. Both the features are extracted from each region of image. The RBGL and Min-Max value can be defined as:

$$RBGL = \sqrt{\sum_{i=1}^{9} Pi} \qquad ----(4)$$

$$Min = \min(Pi)0 \qquad ----(5)$$

$$Max = \max(Pi) \qquad ----(6)$$

Where Pi (i=1, 2, 3, -------, 9) is pixels of 3*3 image region.

The β value features are calculated by using square root of sign difference and it can be defined as:

$$\beta = \sqrt{SD} \qquad ----(7)$$

Where, SD is sign difference features of each 3*3 regions of image.

The MD, SD, β value features are used for rotation invariant texture classification and Min-Max value, RBGL features are used for illumination invariant texture classification.

The block diagram of texture classification algorithm using AGLV method is shown in figure 2. It contains three important Steps such as, Pre-processing Module, Feature Extraction Module and Classification Module. The pre-processing module removes the noise and enhances the image quality. It also changes the scale of both training and test image. Feature extraction module divide the image into 3*3 regions and extract Sign Difference (SD), magnitude difference (MD), RBGL, Min-Max value, β-value features from each region of image. All these features are combining together and used to generate the histogram. Finally, histogram features are used as input to the classification module. The K-Nearest Neighbours and Naïve Bayes classifier use these histogram features to generate the result.

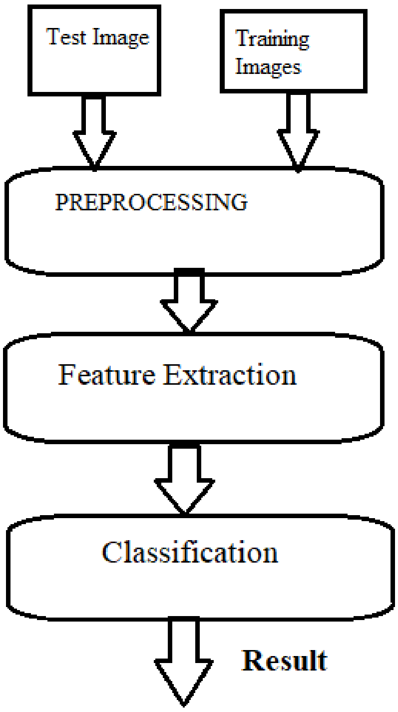

Fig. 2 Block Diagram of Texture Classification

III. EXPERIMENT RESULT

To evaluate the performance of proposed AGLV method experiment are carried out on three standard texture databases namely, Kylberg, Brodatz and Kth-Tips. The proposed AGLV method is developed in MATLAB R2015 and uses KNN and NB classifier for classification of texture image. Both the classifier used in this research work use different scale of images. The experiment is conducted as follows:

C. Performance Rate

Performance of proposed AGLV method is evaluated using following formula:

$$PR = \frac{\text{Number of Correctly idetified images}}{\text{Total Number of Images}} \quad --(8)$$

D. Texture Classification

This Research work use Kylberg texture database [19] to test the performance of proposed AGLV method against normal texture image. The kylberg texture database is divided into two parts training and testing. Figure 3 shows the sample images of kylberg texture database.

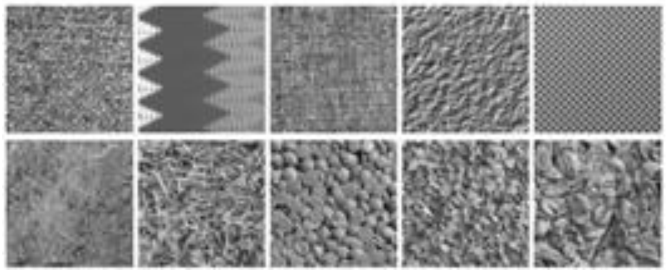

Fig. 3 Sample Images of Kylberg Texture Database

The kylberg texture database contains 28 classes of texture images. Due to large size of image database this research work randomly select only 11 classes of texture images. All images in this database are gray scale JPEG format images. The result of AGLV method using Kylberg texture database is given in table I.

TABLE I PERFORMANCE OF AGLV METHOD USING KYLBERG DATABASE

kylberg database		**KNN Classifier**	**NB Classifier**
Sr.No.	**Image Class**	**Performance Rate**	**Performance Rate**
1	Blanket1	100.00%	100.00%
2	Blanket2	100.00%	20.00%
3	Canvas1	100.00%	100.00%
4	Cealing1	100.00%	100.00%
5	Cealing2	100.00%	100.00%
6	Cushion1	100.00%	100.00%
7	Floor1	100.00%	100.00%
8	Floor2	100.00%	100.00%
9	Grass	80.00%	100.00%
10	Rice1	100.00%	100.00%
	Average	98.00%	92.00%

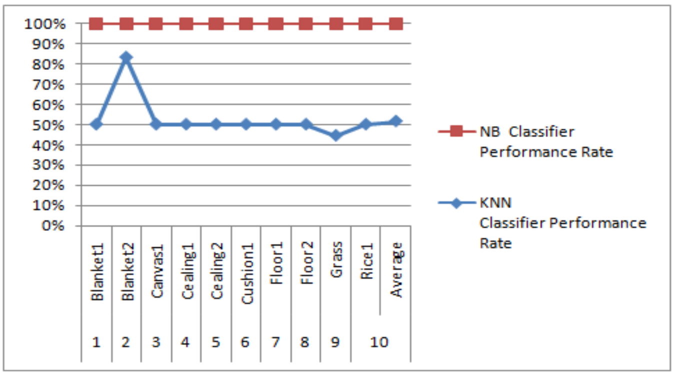

Fig. 3 Graphical representation of performance of AGLV method

The result of AGLV method using KNN classifier is 98.00% and it is higher as compare to NB classifier. The result given in table 4.1 proves that, the AGLV method is significantly outperform against texture classification using normal texture image.

E. Rotation Invariance

All Brodatz texture database [20] is widely used for rotation invariant texture classification. It has 13 classes of texture images. Each class contains 7 images captured in different rotation angle. A classifier is trained using images captured in 0o angle from each class and testing is performed using texture image rotated in six different angles. Figure 4 shows the sample images of brodatz texture database. The result of AGLV method using Brodatz database is given in table II.

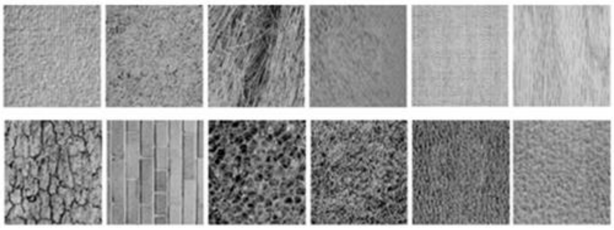

Fig. 4 Sample images of Brodatz Database

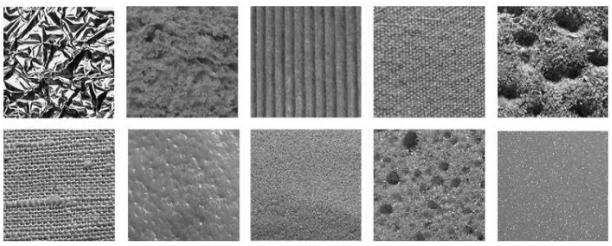

Fig. 6 Sample images of Kh-Tips Database

TABLE II PERFORMANCE OF AGLV METHOD USING BRODATZ DATABASE

Brodatz Database		**KNN Classifier**	**NB Classifier**
Sr.No.	**Image Class**	**Performance Rate**	**Performance Rate**
1	Bark	50.00%	83.33%
2	Brick	100.00%	100.00%
3	Bubbles	66.66%	100.00%
4	Grass	100.00%	100.00%
5	Leather	100.00%	83.33%
6	Pigskin	33.33%	66.66%
7	Raffia	50.00%	100.00%
8	Sand	00.00%	100.00%
9	Straw	50.00%	66.66%
10	Water	50.00%	83.33%
11	Weave	00.00%	100.00%
12	Wood	100.00%	100.00%
13	Wool	83.33%	100.00%
	Average	60.23%	91.02%

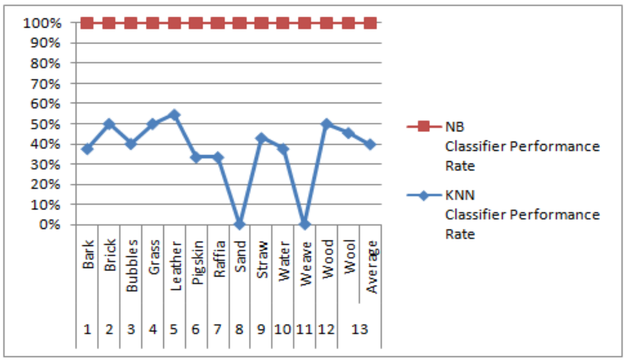

Fig. 5 Graphical representation of AGLV method using Brodatz Database

Experiment result prove that, the AGLV method achieves higher classification result 91.02% using NB classifier and it is higher as compare to KNN classifier. From table 4.3 it is clear that, the AGLV method is much more robust as compare to original LBP method. it achieves higher result in rotation invariant texture classification using Brodatz texture database.

F. Illumination Invariance

To test the illumination invariance of proposed AGLV method Kth-Tips texture database[21] is used. This database contains 10 classes of texture images and all images are captured in three different illumination condition (from the front, from the side at roughly 450 and from the top at roughly 450). In addition to this, all images in this database are captured under 3 different poses (frontal, rotated left 22.50 and rotated right 22.50). There are total 81 images for each texture class. Figure 3.6 shows the sample images of Kth-Tips database.

To test the illumination invariance of proposed AGLV method, this research work uses only nine images of one scale from each class. The training images contain only 10 images (one image from each class) and testing images contain only 80 images (8 images from each class). Table III list the experiment result of AGLV method using Kth-Tips database.

TABLE III PERFORMANCE OF AGLV METHOD USING KTH-TIPS DATABASE

Kth-Tips Database		KNN Classifier	NB Classifier
Sr.No.	**Image Class**	**Performance Rate**	**Performance Rate**
1	Class 06	75.00%	00.00%
2	Class 15	100.00%	87.50%
3	Class 20	00.00%	00.00%
4	Class 21	37.50%	12.50%
5	Class 42	62.50%	37.50%
6	Class 44	25.00%	50.00%
7	Class 46	50.00%	00.00%
8	Class 48	25.00%	37.50%
9	Class 55	50.00%	37.50%
10	Class 60	00.00%	25.00%
	Average	42.50%	28.70%

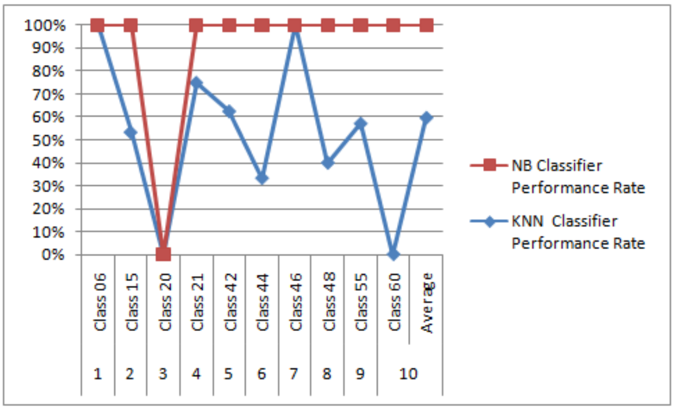

Fig. 7 Graphical representation of AGLV method using Kth-Tips Database

The AGLV method using KNN classifier gives 42.50% results and it is higher as compare to NB classifier. The AGLV method easily captured illumination invariant texture information. From the table 4.1 it is clear that, the AGLV method using Kth-Tips database perform better for illumination invariant texture classification.

IV. CONCLUSIONS

This research work address the limitations of LBP method and proposed new method based on LBP called Average Gray Level Value method for texture classification. it capture more detail local texture information from image. Experiment result obtained from three standard texture databases clearly shows that, the AGLV method gives an effective and efficient approach for texture classification with high discrimination ability. It gives impressive result for rotation invariant and illumination invariant texture classification.

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