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Median Gray Level Value for Texture Classification

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ABSTRACT

A new texture feature extraction method proposed in this paper called Median Gray Level Value method. It is an effective texture classification method due to its high discrimination capability and low computational complexity. The MGLV method divides the image into 3*3 region and compares the pixel intensity value with median value of region. It extracts various local texture features from image. These are median features (MF), Symmetric Intensity Difference (SID) features, $\delta_1, \delta_2, \delta_3, \delta_4$ features. All these features are robust to rotation invariant and illumination invariant texture classification. The MGLV method use K-Nearest Neighbors (KNN) and Naïve Bayes (NB) classifier for texture classification. Experiment result show that, the proposed MGLV method outperform for classification of normal texture image. It gives 92.00% result using Kylberg texture database. This indicate that MGLV method extract more detail texture information of image. Experiment result also shows more distinctive performance for rotation invariant and illumination invariant texture classification. It gives 89.74% result for rotation invariant texture classification using Brodatz texture database and 41.25% result for illumination invariant texture classification using Kth-Tips texture database.

Keywords — Texture Classification, LBP, Median Gray Level Value, Rotation invariant, Illumination invariant.

I. INTRODUCTION

Texture classification means assigning unknown texture image to one of the known texture class. One of the most critical tasks in texture classification is that, rotation invariance and illumination invariance. Texture classification algorithm is used in many image processing application like, medical image analysis, pattern recognition, biometrics, content based image retrieval, remote sensing, industrial inspection and document analysis [1]. As the demand of such applications increases, texture classification received more attention over the last several decades. There are lots of texture classification methods developed by researcher that include GLCM [2], LBP [3], Gaussian Markov Random Field [4], and Wavelet Transform [5]. Among these methods, we mainly focused on LBP method due to its simplicity and less computational complexity.

Original LBP is proposed by ojala et. al. in [6] for extracting local texture features from image. Moreover, LBP represent only sign difference between central pixel and its neighbouring pixel of region. Binary pattern is obtained at pixel location by thresholding the central pixel intensity with surrounding pixel intensity. The concept of original LBP is shown in figure 1. The LBP method converts this binary pattern to decimal number and uses it to label the region of image. Finally, LBP method generates the histogram features from the label of all image regions. LBP histogram features are used for texture classification. In addition to this, original LBP method is very sensitive to variation in image rotation and illumination. To solve this problem, this paper proposed a new method based on LBP called Median Gray Level Value (MGLV) method.

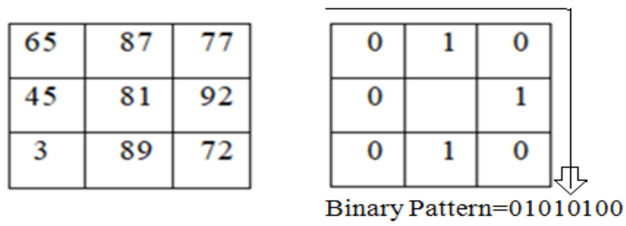

Figure 1: Concept of Original LBP.

The MGLV method effectively extracts dominant local texture features from image. The major difference between LBP and MGLV method is that, LBP uses only sign difference. The MGLV method divides the image into 3*3 region and extracts median features (MF), Symmetric intensity difference (SID) features, $\delta_1, \delta_2, \delta_3, \delta_4$ features from each region of image. All these features are combining together to generate the histogram. The histogram features are used as input to the classifier. All these MGLV features are robust to rotation invariant and illumination invariant texture classification. Detail description of MGLV method is given in section 3. The K-Nearest Neighbours (KNN) and Naïve Bayes (NB) classifier use these statistical features for texture classification. Experiment result on Kylberg[7], Brodatz[8] and Kth-Tips[9] database show that the MGLV method perform well and give excellent result for texture classification.

The rest of this paper is organized as follows. Section 2 gives the detail about LBP variants. Detail description of proposed MGLV method is given in section 3. The experiment result is given in section 4. Finally, section 5 gives the conclusion of this paper.

II. RELATED WORK

From the previous discussion of LBP method it is clear that, LBP is simple and widely used texture descriptor. It gives the information about sign difference. Further to this, various LBP variants are developed by researcher to improve the performance of original LBP method. Different aspect of original LBP method is considered in LBP variants. In this section, a brief review on LBP variants is given below.

An interesting LBP extension proposed by Li et. al. called dynamic threshold local binary pattern (DTLBP) [10]. It use mean value of neighbouring pixels and maximum contract between the neighbouring pixels to compute the feature vector. Local ternary pattern (LTP) [11] is another LBP extension use three states to extract difference between central pixel and neighbouring pixels. The author reported that both DTLBP and LTP are less sensitive to noise as compare to original LBP method.

Local derivative pattern (LDP) proposed in [12] use the features of higher order and represent more information than original LBP approach. Davarzani et. al. proposed in [13] weighted and adaptive LBP-based texture descriptor. It handled the issue of various LBP based approach such as invariance to scaling and rotation viewpoint variations. Elongated binary pattern [14] (ELBP) use an elliptical neighbourhood system and retain structural information in image. Jin et. al. [15] proposed new method based on LBP called improved local binary pattern (ILBP). It compares the intensities of neighbouring pixels with local mean pixel intensities. This reduces the effect of image noise.

Another interesting LBP variant proposed by Li et. al. is extended local binary pattern [16]. This method introduces two different features are pixel intensities and differences. Experiment result shows that significant improvement in texture classification as compare to original LBP method.

III. MEDIAN GRAY LEVEL VALUE

The performance of original LBP method is limited for rotation invariant and illumination invariant texture classification. To overcome this LBP problem, proposed MGLV method use median value to extract robust local texture features from each region of image. These features give excellent result for rotation invariant and illumination invariant texture classification.

A. *Feature Extraction with MGLV Method*

The MGLV method divides the image into 3*3 region. It performs thresholding operation by comparing median value of region with all pixel intensity value of region. The MGLV method generates median binary pattern using thresholding operation and convert it into decimal number to label the each region of image. All the labels of image regions are used to generate histogram features. The thresholding operation performed by MGLV method can be defined as:

$$MF = \sum_{i=1}^{9} f(P_i)\, 2^i \quad ------(1)$$

$$f(P_i) = \begin{cases} 1, & \text{if } P_i \geq med \\ 0, & \text{Otherwise} \end{cases}$$

Where, MF is median features, med is median value of 3*3 region, Pi (i=1, 2, 3, -------, 9) indicate pixel intensity value of 3*3 region. The function f (Pi) performs thresholding operation and generate median binary pattern. In addition to this, MGLV method extract symmetric intensity difference (SID) features, $\delta_1, \delta_2, \delta_3, \delta_4$ features from each region of image. All these features can be defined as:

$$SID = \sum_{i=1}^{9} |P_i - Med| \quad ------(2)$$

$$\delta_1 = Min(P_i) \quad --------(3)$$

$$\delta_2 = Max(P_i) \quad --------(4)$$

$$\delta_3 = \sum_{i=1}^{9} (P_i) \quad --------(5)$$

$$\delta_4 = \sqrt{\sum_{i=1}^{9} (MF)} \quad ------(6)$$

Where SID is symmetric intensity difference between median value (med) and pixel intensity value Pi (i=1, 2, 3, -------, 9) of 3*3 region. δ_1 and δ_2 extracts minimum and maximum pixel intensity value from each 3*3 region of image. δ_3 extracts gray level value from each region of image. Finally, δ_4 extracts square root value of median features (MF) to label the each region of image.

The proposed MGLV method extracts more detail texture information from image using all the features defined by equation 1 to equation 6. The median value makes the MGLV method more robust to rotation invariant and illumination invariant texture classification. The Median Features (MF), Symmetric Intensity Difference Features (SID) and δ_4 features of MGLV method are helpful for rotation invariant texture classification and $\delta_1, \delta_2, \delta_3$ features are helpful for illumination invariant texture classification.

B. *Block Diagram of MGLV Method*

The first step in MGLV method is pre-processing. It changes the scale of all training and test image to enable faster feature extraction process. The pre-processing module also removes the noise from image and enhances the image quality. In second step, the MGLV method extract local texture features from all regions of image and combine together to generate the histogram features. All these histogram features are used as input to classifier. The K-Nearest Neighbours (KNN) and Naïve Bayes (NB) classifier use these histogram features for classification of texture image and generate the result as class name. Figure 2 shows the block diagram of MGLV method.

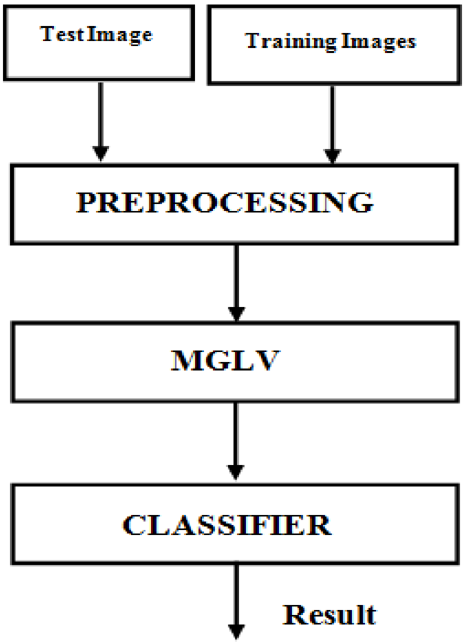

Figure 2: Block Diagram of MGLV Method.

IV. EXPERIMENT RESULT

This paper illustrates the efficiency of proposed MGLV method by carried out the experiment on different texture database. The databases used in the experiment are:

C. Kylberg Texture Database

The Kylberg texture database is used for classification of normal texture image. It contains total 28 classes of texture image. Due to large size of image database, training and testing is performed using randomly selected 11 classes of images. All the images in this database are gray scale images. Figure 3 shows the sample images of kylberg database.

D. Brodatz Texture Database

The Brodatz texture database is used for rotation invariant texture classification. it is built from 13 texture classes. Each class contains seven images rotated in different angle. A classifier is trained using 0^o angle images from each class and testing is performed using rotated images (six images) from each class. Testing set contains total 78 images and training set contains total 13 images. Figure 4 shows the sample images of brodatz database.

E. Kth-Tips Texture Database

The Kth-Tips texture database is used for illumination invariant texture classification. It contains 10 texture classes of images. To test the illumination invariance of MGLV method, we select only one scale of images from each class. The training of classifier is done by using only one image from each class and testing is performed using eight images from each class. There are total 10 images in training set and 80 images in testing set. Figure 5 shows the sample images of Kth-Tips database.

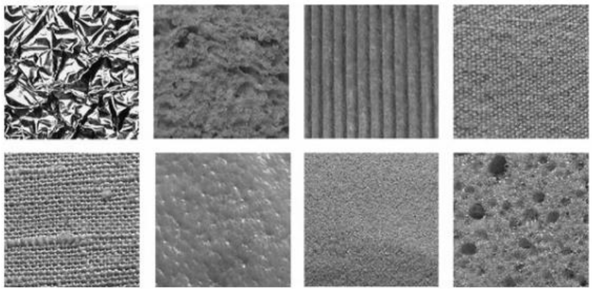

Figure 5: Sample images of Kth-Tips Database.

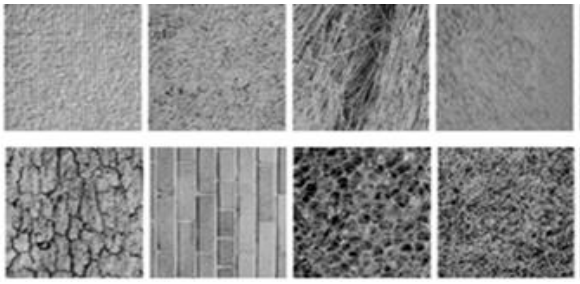

Figure 4: Sample images of Brodatz Database.

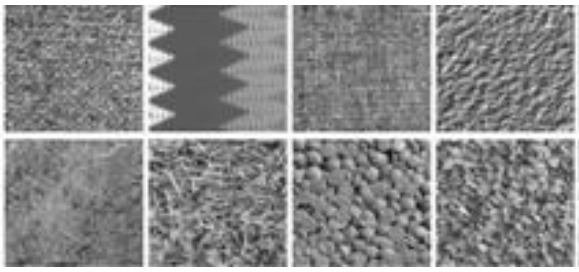

Figure 3: Sample images of Kylberg Database.

The MGLV method use K-Nearest Neighbors (KNN) and Naïve Bayes (NB) classifier for texture classification and the result is given in table 1 to table 3.

TABLE 1: PERFORMANCE OF MGLV METHOD USING KYLBERG DATABASE

kylberg database		**KNN Classifier**	**NB Classifier**
Sr.No.	**Image Classes**	**Result**	**Result**
1	Blanket1	100.00%	100.00%
2	Blanket2	20.00%	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	90.00%	92.00%

TABLE 2: PERFORMANCE OF MGLV METHOD USING BRODATZ DATABASE

Brodatz Database		KNN Classifier	NB Classifier
Sr.No.	Image Classes	Result	Result
1	Bark	83.33%	83.33%
2	Brick	83.33%	83.33%
3	Bubbles	83.33%	100.00%
4	Grass	100.00%	100.00%
5	Leather	83.33%	83.33%
6	Pigskin	66.66%	66.66%
7	Raffia	83.33%	100.00%
8	Sand	33.33%	100.00%
9	Straw	33.33%	50.00%
10	Water	83.33%	100.00%
11	Weave	100.00%	100.00%
12	Wood	100.00%	100.00%
13	Wool	100.00%	100.00%
	Average	79.84%	89.74%

TABLE 3: PERFORMANCE OF MGLV METHOD USING KTH-TIPS DATABASE

Kth-Tips Database		KNN Classifier	NB Classifier
Sr.No.	Image Class	Result	Result
1	Class 06	62.50%	00.00%
2	Class 15	75.00%	62.50%
3	Class 20	25.00%	00.00%
4	Class 21	25.00%	12.50%
5	Class 42	75.00%	37.50%
6	Class 44	12.50%	87.50%
7	Class 46	25.00%	00.00%
8	Class 48	50.00%	37.50%
9	Class 55	37.50%	37.50%
10	Class 60	25.00%	62.50%
	Average	41.25%	33.75%

TABLE 4: RESULT OF MGLV METHOD USING DIFFERENT DATABASE

Database	Result	
	KNN Classifier	NB Classifier
Kylberg	90.00%	92.00%
Brodatz	79.84%	89.74%
Kth-Tips	41.25%	33.75%

Table 1 list the classification result of MGLV method using kylberg texture database. It shows that, MGLV method significantly outperform for classification of normal texture image. The average result given by MGLV method using NB classifier is 92.00%. The average result of rotation invariant texture classification (Brodatz database) is also given in table 2. The MGLV method using NB classifier gives 89.74% result. From the result, it is clear that the MGLV method performs well and gives excellent result for rotation invariant texture classification. Table 3 shows 41.25% result (using KNN classifier) for illumination invariant texture classification. From the result we conclude that, the MGLV method is robust for illumination invariant texture classification. Table 4 shows the result of MGLV method using different texture database and compare with each other. The best average result reported by MGLV method is 92.00% for kylberg texture database.

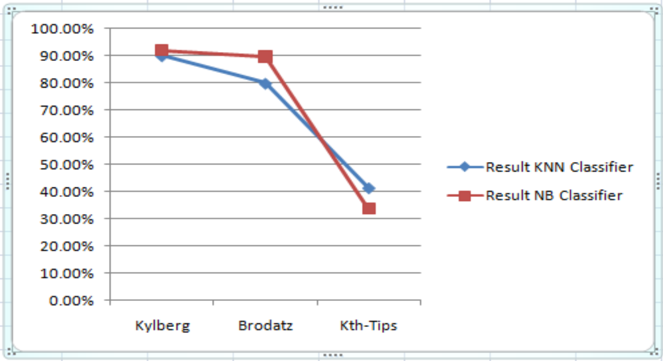

Figure 6: Result of MGLV method using different texture database.

V. CONCLUSIONS

This paper introduced a new texture classification approach based on LBP called median gray level value (MGLV) method. The MGLV method divides the image into 3×3 regions. It considers all the pixels of region to extract local texture features from image. Rotation invariance and illumination invariance of MGLV method is tested using standard texture database. Experiment result shows that, the MGLV method is very effective for classification of normal texture image. It also gives excellent result for rotation invariant and illumination invariant texture classification.

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