Texture Feature Extraction Using Improved Completed Robust Local Binary Pattern for Batik Image Retrieval

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Abstract

One of the robust texture feature extraction methods is Local Binary Pattern (LBP). LBP is a simple but efficient method and gray-scale invariant. Some studies have been proposed to improve the performance of LBP, such as Completed Robust Local Binary Pattern (CRLBP). CRLBP is proposed by Zhao to overcome the weaknesses of CLBP that is sensitive to noise. However, CRLBP is not invariant to rotation. From that problem, in this study, a new approach method of CRLBP is proposed. That proposed method is called Improved Completed Robust Local Binary Pattern (ICRLBP). In ICRLBP algorithm, CRLBP algorithm will be inserted by LBPROT algorithm. LBPROT is one of improved LBP methods that proposed to overcome the LBP weakness which is not rotation invariant. Inserting LBPROT into CRLBP is simply carried out by shifting the binary value obtained from CRLBP to get the smallest integer value. The performance of ICRLBP is evaluated in content-based image retrieval system using 4 datasets, namely Batik, Textile, Brodatz, and Corel datasets. The result experiments show that the average of precision, recall, and speed of ICRLBP using Modified Canberra distance and M_C feature increased by 14.28%, 13.52%, and 3 times, respectively. Whereas, the average of precision, recall, and speed of ICRLBP using L1 distance and S_M_C feature increased by 21.14%, 20.03%, and 56 times, respectively. It show that ICRLBP is proven can improve the performance of CRLBP.

Keywords: *Batik, Completed Robust Local Binary Pattern, Content-based Image Retrieval, Rotation Invariant, Texture Feature Extraction*

1. Introduction

In computer vision and pattern recognition, texture is one of important feature to analyze various types of image. Texture feature can be used for classification, segmentation, or retrieval. Many studies have proposed various methods to analyze texture in images. Those methods are Gray Level Co-occurrence Matrix (GLCM) that is texture feature extraction method based on co-occurrence of grey-level intensity [1], multi-level wavelet transform used to extract the texture of textile images for emotional predicting [2], co-occurrence matrices of sub-band image that is combination method of wavelet and GLCM to extract texture feature of Batik images [3], Enhanced Micro-Structure Descriptor (EMSD) that is image feature descriptor extracting texture, color, and shape features simultaneously [4], Local Binary Pattern (LBP) used to extract the texture feature on Brodatz images [5], etc.

LBP is one of robust texture feature extraction methods proposed by Ojala [5]. LBP is a simple but efficient method to represent texture feature [6]. LBP operator involves only a few neighbor pixels with simple calculation operation. Moreover, LBP is a gray-scale invariant method, not affected to uneven illumination image, because LBP describes texture locally.

T. Ojala proposed LBP for the first time to extract texture feature on Brodatz dataset that consist of 9 classes. The performance of LBP has been compared with other texture feature extraction methods, such as Gray-level Difference method, Law’s texture measure, and Center-symmetric Covariance measure [5]. That study indicated that LBP can achieve the lowest error rate compared with other texture feature extraction methods, namely 2.3% for 32x32 pixels in size images, and 12.5% for 16x16 pixels in size image.

Rotation invariant LBP (LBPROT) has been proposed by Pietikäinen to improve the performance of LBP [7]. The performance of LBPROT has been evaluated on Brodatz dataset that consist of 15 classes. Each image in dataset was rotated at seven different angles. For training data each image was rotated at

11°, while for testing data each image was rotated at 30°, 60°, 90°, 120°, 150°, and 200°.The LBPROT error rate was not quite satisfactory, namely 39.2% for 64x64 pixels in size images, and 47.7% for 32x32 pixels in size image. However, when LBPROT was combined with local variance feature (VAR), LBPROT/VAR can achieve quite low error rate namely 10.1% for 64x64 pixels in size images, and 24.1% for 32x32 pixels in size image. That result indicated that the performance of LBPROT can be increased when it is combined with local contrast feature.

Completed Local Binary Pattern (CLBP) has been proposed by Guo to improve the performance of LBP [8]. The weakness of LBP is some different patterns of local structure can have the same LBP code. Because of that, Guo proposed the new local feature, namely CLBP_Sign (CLBP_S), CLBP_Magnitude (CLBP_M), and CLBP_Center (CLBP_C). CLBP_S has the same principle with LBP, which CLBP_S represents a value that indicate whether the intensity of the neighbor pixels are lower or higher than the intensity of the center pixel. While CLBP_M represents the value of the local difference magnitude between the intensity of neighbor pixels and the intensity of center pixel. CLBP_C represents the value of the gray-level intensity of center pixel to the average gray-level intensity of the entire image. The performance of CLBP was evaluated on Outex dataset that consists of 24 classes, and CUReT dataset that consists of 61 classes. From the result of that experiment indicated that CLBP can increase the average accuracy of 6.67% compared with LBP.

Even so, CLBP has weakness namely sensitive to noise, because the center pixel intensity local is used as threshold directly. Zhao has proposed Completed Robust Local Binary Pattern (CRLBP) to overcome the weakness of CLBP [9]. CRLBP does not use the intensity of center pixel as threshold but it is replaced with the Weighted Local Gray Level (WLG) or average of local gray-level intensity. The performance of CRLBP was evaluated on Outex dataset that consists of 24 classes, CUReT dataset that consists of 61 classes, UIUC dataset that consists of 25 classes, and XU_HR dataset that consists of 25 classes. From the result of that experiment indicated that CRLBP can increase the average accuracy of 2.5% compared with CLBP.

CRLBP, however, has weakness namely it is not rotation invariant. Therefore, in this study the proposed method to overcome that weakness is proposed. The proposed method is Improved CRLBP (ICRLBP). ICRLBP insert the LBPROT algorithm into CRLBP algorithm. CRLBP_M calculates the local variance feature, since it calculate the differences magnitude between the intensity of neighbor pixels and the intensity of center pixel. Thus, inserting LBPROT algorithm into CRLBP algorithm is expected can improve the performance of CRLBP, in order to be rotation invariant. To evaluate the performance of ICRLBP compared to CRLBP, ICRLBP is evaluated in content-based image retrieval system.

2. Dataset

Four image datasets is used for evaluating the performance of ICRLBP, namely Batik, textile, Brodatz, and Corel datasets. The size of Batik, textile, and Brodatz image is 128x128 pixel, whereas the size of Corel image is 80x80 pixel in JPEG format. Batik and Brodatz dataset consist of 112 images, whereas textile and Corel dataset consist of 50 images. Each image of each dataset as one class is rotated by 5°, 10°, 15°, 20°, 25°, 30°, 35°, 40°, 45°, 50°, 55°, 60°, 65°, 70°, 75°, 80°, 85°, 90°. Therefore, there are 18 images in each class. The examples of images in one class are shown in Fig.1.

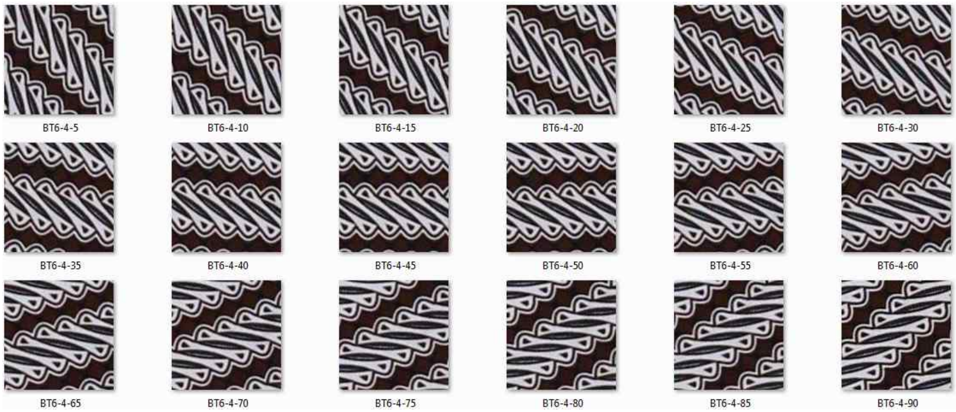

Figure 1. Examples of images in one class of Batik dataset.

Figure 2. Example of Batik dataset.

Figure 3. Example of Textile dataset.

Figure 4. Example of Brodatz dataset.

Batik and textile datasets are obtained from the Laboratory of Intelligent Computation and Vision, Institut Teknologi Sepuluh Nopember. Brodatz dataset is obtained from (http://sipi.usc.edu/database/database.php?volume=textures). Corel dataset used in this study is Corel 5,000 which is obtained from (http://www.ci.gxnu.edu.cn/cbir/Dataset.aspx). Corel 5,000 consists of 50 categories, and each category consists of 100 images. But in this study, just 1 image of each category is used that is chosen randomly. Batik, textile, Brodatz, and Corel datasets is showed in Fig. 2-5 respectively.

Figure 5. Example of Corel dataset.

Batik is traditional pattern on fabric drawn with traditional method [10]. Batik has been recognized by UNESCO as one of the indigenous cultural heritage of Indonesia, on October 2, 2009. Batik, Textile and Brodatz datasets contain images having strong texture charactericties, which is important to investigate in this study. Besides images with strong texture characteristics, experiments with some images having combination of color, shape and texture characteristics, such as in Corel dataset, is also performed.

3. Completed Robust Local Binary Pattern

Completed Robust Local Binary Pattern (CRLBP) is an improved method of Completed Local Binary Pattern (CLBP), so that CRLBP has the same basic principle with CLBP in extracting texture feature. The basic principle is texture represented locally based on center pixel intensity and local difference sign-magnitude intensity of neighbor pixels to the thresholding value. In CLBP, the thresholding value is the center pixel intensity. The local difference can be formulated as defined in Eq. (1), where $s_{p,R}$ is sign, $m_{p,R}$ is magnitude, P is the total number of involved neighbor pixels, R is radius between center pixel and neighbor pixels, I_c is value of center pixel intensity, $I_{p,R}$ is value of p^{th} involved neighbor pixel intensity ($p = 0,1,\dots,P-1$) with radius R.

$$d_{p,R} = s_{p,R} \cdot m_{p,R}, \quad \begin{cases} s_{p,R} = sign\ (d_{p,R}) \\ m_{p,R} = |d_{p,R}| \end{cases} \tag{1}$$

where,

$$s_{p,R} = s(I_{p,R} - I_c) \text{ dan } m_{p,R} = |I_{p,R} - I_c|$$

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

The calculation illustration of local difference is shown in Fig.6. Fig.6 show that the difference vector is [-40,-30,50,-5,10,40,25,-25], then sign vector is [-1,-1,1,-1,1,1,1,-1] and magnitude vector is [40,30,50,5,10,40,25,25]. Those sign vector and magnitude vector are transformed to get the binary values of sign vector and magnitude vector. After that, all binary values of sign vector and magnitude vector are converted to decimal value, as illustrated in Fig.7. From Fig.7, the sign feature is 142 that is calculated from 2+4+8+128.

(a)

10	20	100
25	**50**	45
75	90	60

(b)

-40	-30	50
-25		-5
25	40	10

(c)

40	30	50
25		5
25	40	10

(d)

-1	-1	1
-1		-1
1	1	1

Figure 6. Illustration of local difference. (a) Original Image. (b) Local difference ($d_{p,R}$). (c) Magnitude vector. (d) Sign vector.

(a)

10	20	100
25	**50**	45
75	90	60

(b)

-1	-1	1
-1		-1
1	1	1

(c)

0	0	1
0		0
1	1	1

(d)

2^5	2^6	2^7
2^4		2^0
2^3	2^2	2^1

(e)

0	0	128
0		0
8	4	2

Figure 7. (a) Original Image. (b) Sign vector. (c) Binary value of sign vector. (d) Weight to convert binary to decimal. (e) Decimal value of sign vector.

The difference between CLBP and CRLBP is their thresholding value. CLBP uses center pixel intensity as threshold but CRLBP does not use the intensity of center pixel as threshold, it is replaced with *Weighted Local Gray Level* (WLG) as defined in Eq. (2).

$$WLG = \frac{\sum_{p=0}^{P-1} I_{p,R} + \alpha I_c}{P + \alpha} \tag{2}$$

Where α is a parameter set by user, I_c, $I_{p,R}$, P, and R are defined as in Eq. (1). As a result, the local difference sign and magnitude of CRLBP are defined as Eq. (3) and (4), respectively.

$$CRLBP\_S = \sum_{p=0}^{P-1} s(I_{p,R} - WLG_c)\, 2^p = \sum_{p=0}^{P-1} s\left(I_{p,R} - \frac{\sum_{i=0}^{P-1} I_{i,R} + \alpha I_c}{P + \alpha}\right) \tag{3}$$

where,

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

Where $I_{i,R}$ is value of i^{th} involved neighbor pixel intensity ($i = 0,1,\dots,P-1$) with radius R from center pixel I_c, I_c, $I_{p,R}$, P, and R are defined as in Eq. (1), α is defined as in Eq. (2).

$$CRLBP\_M = \sum_{p=0}^{P-1} s(m_p - c)\, 2^p \qquad (4)$$

where,

$$m_p = |WLG_p - WLG_c| = \left| \frac{\sum_{i=0}^{P-1} I_{pi,R} + \alpha I_{p,R}}{P+\alpha} - \frac{\sum_{i=0}^{P-1} I_{ci,R} + \alpha I_c}{P+\alpha} \right|$$

P, $I_{ci,R}$, I_c, $I_{p,R}$, and R are defined as in Eq.(1), $I_{pi,R}$ is value of i^{th} involved neighbor pixel intensity ($i = 0,1,\dots,P-1$) with radius R from center pixel $I_{p,R}$. Where as c is threshold calculated of mean value of m_p of a whole image. CRLBP_M is calculated the local variance of WLG.

CRLBP_C operator represents value of center pixel intensity as defined in Eq. (5).

$$CRLBP\_C = s(WLG_c - c_I) \qquad (5)$$

Where c_I is threshold calculated of mean value of *Average Local Gray Level* (ALG) of a whole image. ALG is defined in Eq. (6).

$$ALG = \frac{\sum_{p=0}^{P-1} I_{p,R} + I_c}{P} \qquad (6)$$

That feature value of CRLBP_S, CRLBP_M, and CRLBP_C is plotted to their own histogram. In grayscale image, if the value of P is 8, then histogram of CRLBP_S, CRLBP_M, and CRLBP_C consist of 256, 256, and 2 bin features, respectively. Those histograms can be combined together to get the final histogram of CRLBP.

4. LBPROT

Rotation invariant LBP or LBPROT is invariant rotation LBP algorithm that extract texture feature as shown in Fig. 8. The binary value obtained from texture feature extraction of LBP, before it is converted to decimal value, is shifted until we get the smallest combination of binary value. As a result, LBPROT can be defined in Eq. (7). Where $LBP_{P,R}$ is binary value obtained from texture feature extraction of LBP, and P is the total number of shifted combination that has the same total number of involved neighbor pixels.

$$LBPROT_{P,R} = \min\{ROT(LBP_{P,R}, p)\} \qquad (7)$$

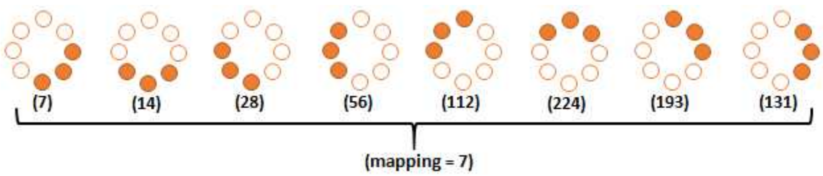

Figure 8. Shifting of a binary value to find the smallest combination.

5. Improved Completed Robust Local Binary Pattern

Improved Completed Robust Local Binary Pattern (ICRLBP) is proposed to improve the performance of CRLBP in order to be rotation invariant. ICRLBP improves the performance of CRLBP by inserting LBPROT algorithm to CRLBP algorithm, as shown in Fig.10.

ICRLBP has the same basic principle and the same operators with CRLBP in extracting texture feature. LBPROT algorithm is inserted after binary value of sign vector and magnitude vector is obtained. LBPROT looks for the smallest combination of binary value of sign vector and magnitude vector in each pixel. Then, the smallest combination of binary value is converted to decimal value. From the decimal value, feature histogram of ICRLBP_Sign (ICRLBP_S), ICRLBP_Magnitude (ICRLBP_M), and ICRLBP_Center (ICRLBP_C) can be plotted.

In grayscale image, if the value of P is 8, then histogram of CRLBP_S, CRLBP_M, and CRLBP_C consist of 36, 36, and 2 bin features, respectively. Those histograms can be combined together to get the final histogram of ICRLBP. Based on Guo [8], there are two ways to combined those histograms, namely concatenate and jointly.

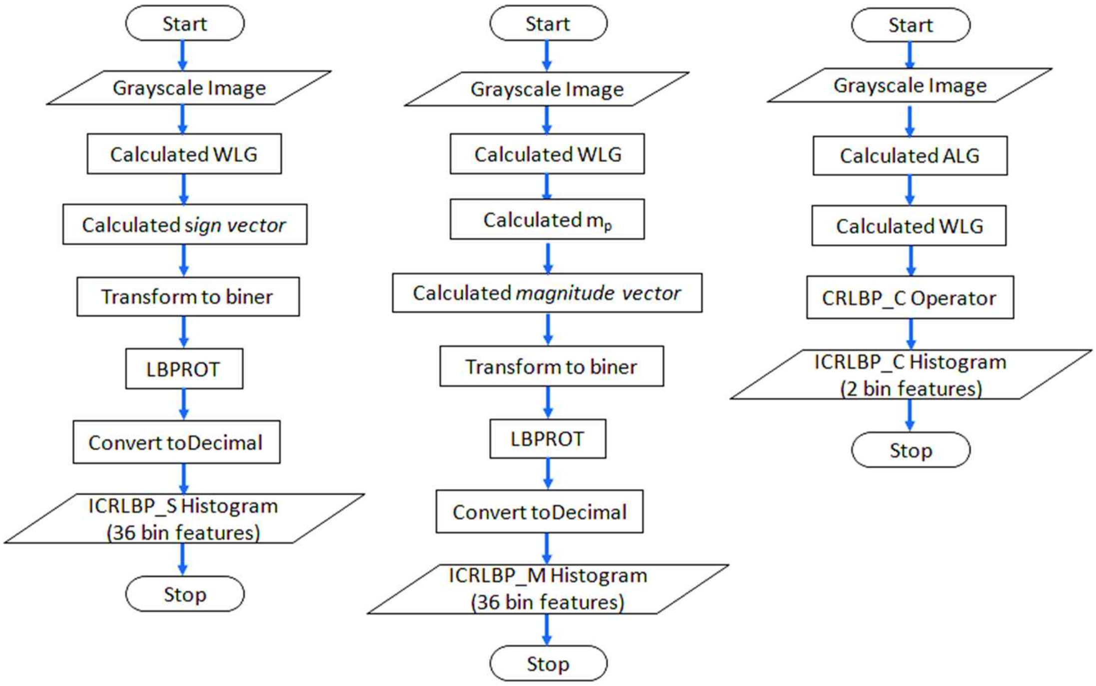

Figure 10. Flowchart of ICRLBP

6. Distance Measure

The similarity between query images and images in the database is measured using L1 and modified Canberra distance [4], that are defined in Eq. (8) and (9), respectively.

$$LD\,(T,Q) = \sum_{i=1}^{F} |Ii - Qi| \quad (8)$$

$$CD\,(T,Q) = \sum_{i=1}^{F} \frac{|Ii - Qi|}{|Ii + \mu I| + |Qi + \mu Q|} \quad (9)$$

Where I is image in the dataset, Q is query image, F is the number of feature vector of each image, $\mu I = \sum_{i=1}^{F} \frac{Ii}{F}$ and $\mu Q = \sum_{i=1}^{F} \frac{Qi}{F}$.

7. Performance Measure

The performance of ICRLBP is measured using precision and recall which are defined in Eq. (10) and (11), respectively.

Precision = I_r/n . 100% (10)

Recall = I_r/m . 100% (11)

Where I_r is the number of retrieved images, *n* is the number of relevant images that must be retrieved, and *m* is the number of all relevant data in the dataset.

8. Result and Discussion

The performance of ICRLBP is evaluated with several scenarios on the four databases. In each scenario, each image of each database become a query image alternately. The total number of image that are retrieved in each retrieval process of one query image is 18 images, because there are 18 images in one class that are rotated in different angles.

The first scenario looked for the optimal feature and the optimal histogram combination. As described in section 5, ICRLBP has three feature histograms, ICRLBP_S, ICRLBP_M, and

ICRLBP_C. Those histogram can be combined in two ways, concatenation and jointly. As a result, there are 11 schemes to combine those feature histograms, namely ICRLBP_S (S), ICRLBP_M (M), ICRLBP_C (C), ICRLBP_S and ICRLBP_M combined concatenately (SM), ICRLBP_S and ICRLBP_C combined concatenately (SC), ICRLBP_M and ICRLBP_C combined concatenately (MC), ICRLBP_S, ICRLBP_M, and ICRLBP_C combined concatenately (SMC), ICRLBP_S and ICRLBP_M combined jointly (S_M), ICRLBP_S and ICRLBP_C combined jointly (S_C), ICRLBP_M and ICRLBP_C combined jointly (M_C), ICRLBP_S, ICRLBP_M, and ICRLBP_C combined jointly (S_M_C). Table 1 show the result of the first scenario. Table 1 indicate that the optimal feature when using Modified Canberra distance is M_C with the value of precision and recall are 77.29% and 73.22%, respectively. Whereas, when using L1 distance, the optimal feature is S_M_C with the value of precision and recall are 77.24% and 73.31%, respectively. Based on those results, in further scenario the feature combinations that are used are M_C and S_M_C.

The second scenario compared the performance of ICRLBP with CRLBP based on the precision and recall. Table 2 indicates the performance of ICRLBP on each dataset and Table 3 indicates the performance of CRLBP on each dataset. From Table 2 and Table 3, it can be seen that the precision and recall of ICRLBP are higher than precision and recall of CRLBP. Table 4 is a comparison of the average precision and recall from Table 2 and Table 3. From Table 4, it can be seen that using Modified Canberra distance with M_C feature the precision and recall of ICRLBP increase of 14.28% and 13.52% respectively, while using L1 distance with S_M_C feature the precision and recall of ICRLBP increase of 21.14% and 20.03%, respectively. Those results indicate that ICRLBP is more rotation invariant than CRLBP, because ICRLBP inserts LBPROT algorithm that is rotation invariant into CRLBP algorithm.

The third scenario compared the performance of ICRLBP with CRLBP based on the value of time consumption. Table 5 indicates the average of time consumption of ICRLBP and CRLBP on each dataset. From Table 5, it can be seen that the time consumption of ICRLBP is faster than CRLBP's. Time consumption of ICRLBP with M_C feature is three times faster than time consumption of CRLBP. Whereas, with S_M_C feature, time consumption of ICRLBP is 56 times faster than time consumption of CRLBP. These results can be achieved because the number of features on ICRLBP_S and ICRLBP_M histogram is fewer than the number of features on CRLBP_S and CRLBP_M histogram. ICRLBP_S histogram has 36 bin features and ICRLBP_M histogram has 36 bin features, while CRLBP_S histogram has 256 bin features and CRLBP_M histogram has 256 bin features.

Table 1. Average precision and recall comparisson of ICRLBP feature

Feature :		S	M	C	SM	SC	MC	SMC	S_M	S_C	M_C	S_M_C
L1	Precision	47.22	52.91	18.51	65.39	49.46	54.87	65.64	71.54	65.64	64.17	77.39
	Recall	44.73	50.13	17.54	61.95	46.85	51.99	62.19	67.77	62.19	60.80	73.31
Canberra	Precision	52.09	62.50	18.53	70.10	54.60	64.54	70.86	66.34	66.11	77.29	73.07
	Recall	49.35	59.21	17.55	66.41	51.73	61.14	67.13	62.85	62.64	73.22	69.22

Table 2. Precision and recall of ICRLBP in each dataset

		Batik		Brodatz		Textile		Corel	
		M_C	S_M_C	M_C	S_M_C	M_C	S_M_C	M_C	S_M_C
L1	Precision	61.86	79.22	53.19	66.24	79.77	84.86	61.86	79.22
	Recall	58.61	75.05	50.39	62.75	75.57	80.39	58.61	75.05
Canberra	Precision	80.75	80.48	65.73	61.87	81.92	69.44	80.75	80.48
	Recall	76.5	76.25	62.27	58.61	77.61	65.78	76.5	76.25

Table 3. Precision and recall of CRLBP in each dataset

		Batik		Brodatz		Textile		Corel	
		M_C	S_M_C	M_C	S_M_C	M_C	S_M_C	M_C	S_M_C
L1	Precision	46.15	61.04	41.81	53.06	63.46	58.46	40.47	52.43
	Recall	43.73	57.83	39.61	50.26	60.12	55.38	38.34	49.67
Canberra	Precision	70.41	17.95	58.88	16.36	62.61	22.44	60.14	18.07
	Recall	66.7	17	55.79	15.5	59.32	21.26	56.98	17.12

Table 4. The average difference of precision recall ICRLBP and CRLBP

Feature	Distance measure	ICRLBP		CRLBP		The diff. of ICRLBP and CRLBP	
		Precision	Recall	Precision	Recall	Precision	Recall
M_C	L1	64.17	60.80	47.97	45.45	16.20	15.35
	Canberra	77.29	73.22	63.01	59.70	14.28	13.52
S_M_C	L1	77.39	73.31	56.25	53.29	21.14	20.03
	Canberra	73.07	69.22	18.71	17.72	54.36	51.50

Table 5. The average difference of ICRLBP and CRLBP time consumption

Dataset	Time Comcuming ICRLBP (s)		Time Comcuming CRLBP (s)		The diff. of CRLBP and ICRLBP time Comsumtion (times)	
	M_C	S_M_C	M_C	S_M_C	M_C	S_M_C
Batik	188	2809	623	182824	3	65
Brodatz	187	2796	613	162235	3	58
Textile	38	514	114	26162	3	51
Corel	38	514	117	26148	3	51
				Average diff. (times)	3	56

9. Conclusion

This study proposed a method to improve the performance of Complete Robust Local Binary Pattern (CRLBP) in order to have rotation invariant ability. The proposed method is called Improved Complete Robust Local Binary Pattern (ICRLBP). ICRLBP improved the performance of CRLBP by inserting LBPROT algorithm to CRLBP algorithm. LBPROT is one of improved LBP methods that proposed to overcome the LBP weakness which is not rotation invariant. Based on evaluation result, the proposed method can achieve higher precision and recall than CRLBP when retrieve 18 images in each dataset. The average value of precision and recall by using ICRLBP features (M_C) and Modified Canberra distance can be improved 14.28% and 13.52%, respectively, compared to CRLBP. Whereas, the average value of precision and recall by using ICRLBP features (S_M_C) and L1 distance can be improved 21.14% and 20.03%, respectively. In addition, the time consuming average of ICRLBP with M_C feature is three times faster than CRLBP. Whereas, using S_M_C feature is 56 times faster. Therefore, we can conclude that ICRLBP method which considers rotation invariant can perform better than CRLBP in image retrieval using Batik, Brodatz, Textile, and Corel image dataset. In the future, a study to compare ICRLBP with other rotation invariant texture extraction methods is required.

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