A New Local Binary Pattern in Texture Classification

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Abstract. The e LBPs extract local structure information by establishing a relationship between the central pixel and its adjacent pixels. However, it is very sensitive to the change of the central pixel .In this paper,we choose a circle with the radius of 1 instead of a single center. The method is proposed for texture classification by comparing the information between the neighbors and the new center pixel. In order to decrease the feature size and increase the classification accuracy, both LBC-like feature and CLBP feature were used in the proposed method .Experiments are carried out on Outex and UIUC databases. The experimental results demonstrate that this method perform effectively.

Keywords: CLBP, LBP, LBC, texture classification.

1 Introduction

The local binary pattern (LBP) descriptor, firstly proposed by Ojala et al [1], is a popular texture feature. It probes texture images by first comparing the greyscale values between a given pixel and its neighboring pixels. Since Ojala's work, Tan and Triggs [2] proposed Local Ternary Pattern (LTP) by extending original LBP to 3-valued codes. Recently, Guo et al [3] proposed the completed LBP (CLBP) by combining the conventional LBP with the measures of local intensity difference and central gray level. Zhao and Huang [4] proposed to use local binary count (LBC) to extract the local neighborhood distribution.

While traditional methods only encode the greyscale values between a given pixel and its neighboring pixels. These methods are sensitive to noise and the results were unsatisfactory. Motivated by the work of Guo et al. [3], Zhao and Huang [4], we proposed in this letter a new pattern to texture information by shaping a new center.This method captured more detailed information by exploring gray-scale properties between neighborhoods and more pixels. Experimental results illustrate that the supplement information can effectively increase the classification accuracy.

D.-S. Huang et al. (Eds.): ICIC 2014, LNCS 8588, pp. 700–705, 2014.

2 Brief Review of the LBP, LBC and the CLBP

2.1 Local Binary Pattern(LBP)

LBP has shown excellent performance in many comparative studies[5]. We can describe the algorithm of LBP in three main steps. 1) The values of neighbor pixels are turned to binary values by comparing them with the central pixel. 2) We encode the binary numbers and then the code is transformed into decimal number. 3) A histogram will be built to represent the texture image.The LBP coding strategy can be described as follows:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p, \qquad s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{1}$$

where g_c represents the gray value of the center pixel and g_p(p=0,…,P-1) denotes the gray value of the neighbor pixel on a circle of radius R, and P is the total number of the neighbors.

2.2 Completed LBP (CLBP)

Guo et al [3] proposed CLBP descriptor to further improve the discrimination capability of LBP descriptor by decomposing the image local differences into two complementary components which named CLBP_S and CLBP_M where the CLBP_S is equivalent to the conventional LBP and the CLBP_M can be defined as follows:

$$CLBP\_M_{P,R} = \sum_{p=0}^{P-1} s(m_p - c)2^P, \qquad m_p = |g_p - g_c| \tag{2}$$

where g_p, g_c and s(x) are defined as in Eqn. (1) ,the threshold c is set as the mean value of m_p.Guo observed that the center pixel also has discriminative information. Thus, they defined an operator named CLBP_C to extract the local central information :

By combining the three operators of the CLBP_S, the CLBP_M and the CLBP_C, significant improvement is made for rotation invariant texture classification.

2.3 Local Bianary Count (LBC)

Zhao and Huang[4] proposed to use a local counting method to encode the local distribution after quantizing local neighbors into two values(0 or 1). In LBC method, they only count the number of value 1's in the binary neighbor sets.

The LBC reveals a cursory encoding method to characterize the local neighborhood distribution and the LBC-like encoding is easy to expand. LBC obtains the same performance as LBP in rotation invariant cases.

3 New Local Binary Pattern

Looking at Fig.1, if we hit the bull's eye, then we got out, rather than have to shoot to the center of the target.

Fig. 1. .Target

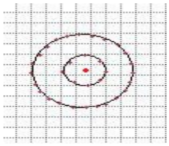

Fig. 2. (P=24,R=3)

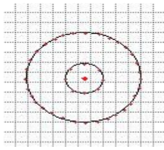

Fig.2.(P=32,R=4)

Motivated by this, we shape a new center, a circle with radius of 1, As illustrated in Fig.2,We shape the new center with 9 pixels or 5 pixels, in other words, it is just 8 or 4 neighbors with a central pixel when the radius equals to 1.

Analyzing LBP from the view point of the local structures, we proposed a new local binary pattern in order to establish a relationship between the neighborhood pixels and the new center. Given a local structure (N=24, R=3), this means that the nearest neighborhood pixels also act as center pixel in the local region. Thus this method explores gray-scale properties between neighborhoods and the central pixel as well as gray-scale properties between neighborhoods and the nearest neighbors.

CLBP combined the three main componentsto to create a joint-histogram. In our method, The new center will generate the histogram as CLBP. For N = 24, the feature size of CLBP (S_MC) is (26+26*2)=78. Therefore, the proposed model will increase the feature size to 9*(26+26*2) =702 or 5*(26+26*2) =390.

As discussed in [4], the micro-structure was not absolutely invariant to rotation under the illumination changes. Therefore, [4] introduced the local binary count (LBC) by abandoning the micro-structure and obtained the same performance as LBP .

Motivated by CLBP and LBC, we applied this idea to our new local binary pattern . To decrease feature size, we can choose m pixels encoded in CLBP, and the rest of 9 or 5 central pixels are encoded in LBC. In this text we choose the original center encoded in CLBP and the 4 or 8 nearest neighbors in LBC. We create this complementary component named CLBP_L by summing the 'LBC' patterns. A simple example is conducted to demonstrate the proposed model In Fig.3

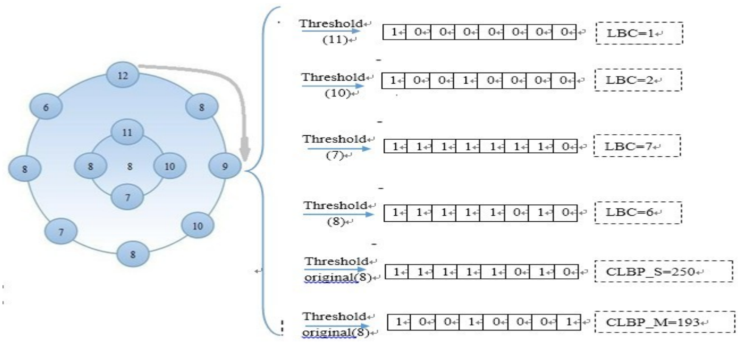

Fig. 3. (P=8,R=2); new center{8,7,10,11,8}

So CLBP_L= $\sum_{p=1}^{n} LBC(g_p)$ =16.

The final feature was a joint-histogram among CLBP_S, CLBP_M, CLBP_C, CLBP_L; such as CLBP_S/M/C_L or CLBP_S_M/C_L;

4 Experimental Results

To evaluate the effectiveness of the proposed method, we carried out a series of experiments on serval representative databases: the UIUC database [6] and Outex database [7].

4.1 The Methods in Comparison

In the experiments, we choose the original center encoded in CLBP and the 4 or 8 nearest neighbors in LBC, the NN classifier were used for all methods here.

4.2 Experimental Results on Outex Database

Table I lists the experimental results by different schemes. Under TC12, "T" represents the test setup of illuminant "t184" and "H" represents "horizon". (O=1,L=4/8) represents that the original center was encoded in CLBP and the 4 /8 nearest neighbors of the new center were encoded in LBC; We could make the following findings. First, CLBP_S_L achieves much better result than CLBP_S in most cases. It is in accordance with our analysis that the new center is more informative than the original center. Second, the comparing between the nearest neighbors and the neighborhood pixels contains additional discriminant information as CLBP_S_L could get much better results than CLBP_S, and CLBP_S/M/C_L gets better results than CLBP_S/M/C.

Table 1. The classification rates (%) on Outex database

	R=2,P=16				R=3,P=24			
	TC10	TC12/T	TC12/H	AVG	TC10	TC12/T	TC12/H	AVG
CLBP_S	89.40	82.26	75.20	82.28	95.07	85.04	80.78	86.96
CLBP_S_L(O=1,L=4)	92.86	86.32	82.57	87.25	96.77	89.24	85.90	90.64
CLBP_S_L(O=1,L=8)	93.20	86.92	82.36	87.45	96.38	88.80	86.78	90.65
CLBP_SM	97.89	90.55	91.11	93.18	99.32	93.58	93.35	95.41
CLBP_SM_L(O=1,L=4)	**98.07**	**92.15**	**92.06**	**94.09**	**99.43**	**95.25**	**94.79**	**96.49**
CLBP_SM_L(O=1,L=8)	98.15	92.04	92.08	94.09	99.30	95.05	94.70	96.35
CLBC_SMC	98.83	93.59	94.26	95.56	98.96	95.37	94.72	96.35
CLBP_SMC	98.72	93,54	93.91	95.39	98.93	95.32	94.53	96.26
CLBP_SMC_L(O=1,L=4)	**98.80**	**94.26**	**94.28**	**95.78**	**99.35**	**96.44**	**95.58**	97.12
CLBP_SMC_L(O=1,L=8)	98.80	94.51	94.10	95.80	99.30	96.30	95.46	97.02

4.3 Experimental Results on UIUC Database

The UIUC texture database contains materials imaged under significant viewpoint variations. In our experiment, *20* training images are randomly chosen from each class while the remaining 20 images are used as the test set. The average accuracy over 100 randomly splits are listed in Table 2. Similar findings to those in part B of section 4 can be found in Table 2. The classification rates were improved significantly with another component to supply LBP.

Table 2. The classification rates (%) on UIUC database

	R=1,P=8	R=2,P=16	R=3,P=24
CLBP_S	54.79	61.04	64.11
CLBP_S_L(O=1,L=4)	60.74	68.05	70.34
CLBP_S_L(O=1,L=8)	60.7	67.99	70.4
CLBP_SM	81.8	87.87	89.18
CLBP_SM_L(O=1,L=4)	**82.43**	**88.34**	**90.40**
CLBP_SM_L(O=1,L=8)	82.62	88.44	90.60
CLBC_SMC	87.64	91.04	91.2
CLBP_SMC	87.61	91.03	91.19
CLBP_SMC_L(O=1,L=4)	**88**	**91.75**	**92.31**
CLBP_SMC_L(O=1,L=8)	88.2	91.85	92.47

5 Conclusions

In this paper, we try to describe the local gray-level distribution by proposing a new center; A LBC-like feature is used in the proposed method. The experiment on two real-captured texture databases illustrated that this new center could effectively improve the classification rates.

Acknowledgment. The authors would like to sincerely thank T. Ojala and Z. Guo for sharing the source codes .This work is supported by the Science and Technology Innovation Outstanding Talent Plan Project of Henan Province of China under Professor De-Shuang Huang (No.134200510025), the National Natural Science Foundation of China (No. 61373105, 61373098 & 61133010).

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