Detecting Computer Generated Images Based on Local Ternary Count[1]

D. Q. Tan[a]*, X. J. Shen[a], J. Qin[a], and H. P. Chen[a,b]

[a] *College of Computer Science and Technology, Jilin University, Changchun, Jilin 130012, China*

[b] *Key Laboratory of Symbolic Computation and Knowledge Engineering of Ministry of Education, Jilin University, Changchun, Jilin 130012, China*

*e-mail: *tandq14@mails.jlu.edu.cn, xjshen@jlu.edu.cn, qinjun15@mails.jlu.edu.cn, chenhp@jlu.edu.cn*

Abstract—Local binary patterns was used to distinguish the Photorealistic Computer Graphics and Photographic Images, however the dimension of the extracted features is too high. Accordingly, the Local Ternary Count based on the Local Ternary Patterns and the Local Binary Count was developed in this study. Furthermore, a novel algorithm is presented based on the Local Ternary Count to classify photorealistic Computer Graphics and Photographic images. The experiment results show that the proposed algorithm effectively reduces the dimension of the classification features and maintains a good classification performance.

Keywords: passive forensics, photographic images, photorealistic computer graphics, local ternary count, support vector machine

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INTRODUCTION

With the rapid growth of image processing softwares and the advancement in digital cameras, there are more and more tampered images with no obvious traces, which generats a great demand for automatic forgery detection algorithms in order to determine the trustworthiness of a candidate image.

The rapid development of Computer Graphics (CG) technologies, a large amounts of PhotoRealistic Computer Generated (PRCG) have been generated by sophisticated computer graphics rendering software, which are difficult to distinguish visually from Photographic IMages(PIM). Examples of PRCG and PIM from Columbia image dataset [1] are shown in Fig. 1.

One of the challenging and immediate problem is to distinguish between PRCG and PIM. Although PRCG is almost indistinguishable from PIM through vision, the differences of access, image content, ray imaging, mode noise or object model, result in a different statistical distribution, such as smoothness, number of colors, histogram continuity and small quantity texture complexity and so on. Generally, PIM change slower in brightness, color, texture and other aspects, and have richer texture level than PRCG. Thus the differences of statistical characteristics can be used as the evidence to effectively detecte PRCG from PIM.

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Passive forensics is the most popular classifying methods [2]. PRCG are detected mainly by extracting statistical characteristics of image. Like Higher-order wavelet statistics [3], Complex dimension characteristics [4], Statistical features of wavelet coefficients on HSV [5, 6], statistical moments of wavelet sub-bands' histogram in DFT domain [7]. Existing methods usually have more than 100 dimensions characteristics. The computational complexity is relatively high.

Local binary patterns (LBP) [8] were used to analyze the image texture features, which has strong ability to distinguish PRCG from PIM in texture classification. However, it has a high complexity and poor robustness. In order to enhance the robustness of texture features, Tan proposed Local Ternary Patterns (LTP) on the basis of LBP [9]. LTP maintained the high computationally efficient, discriminatory power and noise immunity of LBP, nevertheless, it dramatically increased the computational complexity. Local Binary Count (LBC) [10] was proposed by Zhao, which was mainly used for the rough description of image local gray distribution and had simple calculation and strong identification ability. The process of LBC feature extracting is similar to LBP with the reduced encoded information, but results in a slight decrease of accuracy.

Li's method extracts rotation invariant LBP histogram feature from YCrCb color space to detect PRCG from PIM in 2013, which performed well [11]. The disadvantage is the high feature dimension with the size of 236-dimensional, though the LBP histogram features are only extracted from the Y and Cr channel of YCrCb color space.

Fig. 1. PRCG and PIM.

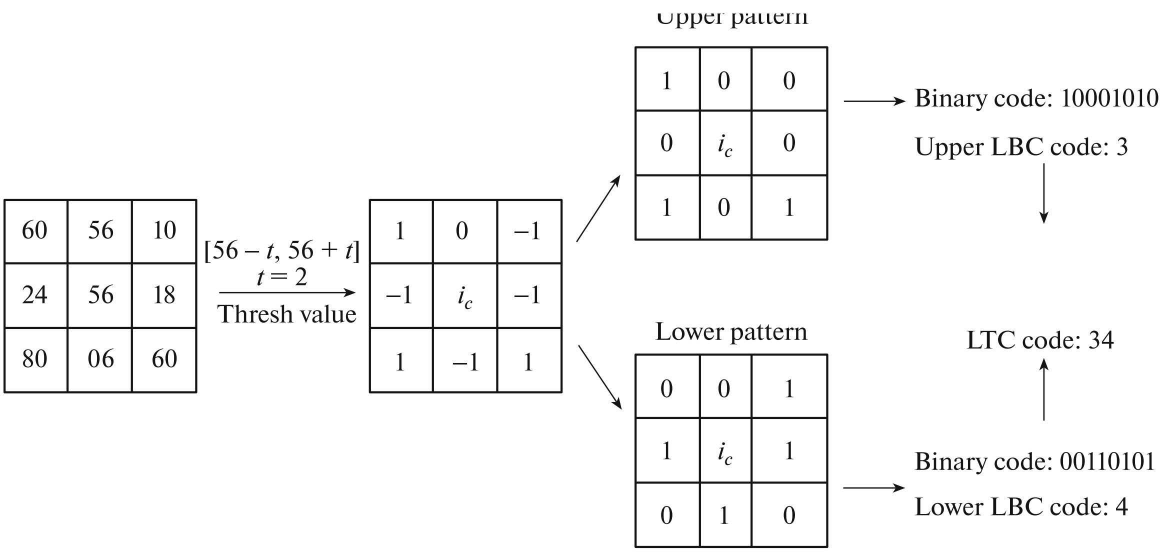

Fig. 2. LTC feature process schematic.

Accordingly, in order to reduce the computational complexity and maintain a high performance, Local Ternary Count (LTC) is developed by improving LBP in this study. And a novel algorithm of detecting PRCG from PIM is proposed based on LTC, which extracts LTC histogram feature from HSV color space and uses SVM to classify PRCG and PIM. The algorithm has lower complexity and performs well.

1. THE STRUCTURE OF LTC FEATURES

The effective description of adjacent pixels' gray value difference, was played a leading role in LBP. And LTP introduced threshold mode on the basis of LBP, to further accurately describe the difference. In order to better show the differences between adjacent pixels of the image and reduce the feature dimension, LTC is detailed described as follows: Firstly, the adjacent pixels' binary codes are calculated according to LTP calculations, and the upper and lower LTC binary codes are obtained; secondly, encode in accordance with the LBC encoding format. The detailed schematic diagram of the LTC coding calculation is shown as Fig. 2.

Based on the large number of trials, examples of PRCG and PIM and corresponding upper LTC normalized histogram of the H channel in HSV color space are shown in Fig. 3. Where in Figs. 3e–3h, the histogram horizontal axis represents LTC feature dimensions and the vertical axis represents each dimension feature corresponding normalized histogram component. LTC histogram reflects the gray value changes between adjacent pixels of the image. The image Figs. 3a, 3c are comparatively smooth images. The left side values of Fig. 3e are relatively large, which shows that most of the differences between adjacent pixels are in the threshold range. Nevertheless, the rest are close to zero, which shows that only few situations of the difference between adjacent pixels are out of the threshold range. This shows that the PIM image is relatively changing slowly and the adjacent pixel values are also relatively close. However, PRCG image Fig. 3c changes relatively intensely by the histogram. We could observe the same appearances in images Figs. 3b, 3d, where PIM image Fig. 3b has a more gradual change. In summary, LTC can be used to detect PRCG and PIM.

2. PRCG DETECTING BASED ON LTC

LTC features are extracted from HSV color space, which are used to detect PRCG and PIM. The basic flowchart of the algorithm is shown in Fig. 4.

2.1. Image Preprocessing

Divide the image dataset into train images and test images, and then both of the two parts are converted into HSV color space and H, S, and V three single-channels of the images are isolated.

2.2. Feature Exaction

For an image $M \times N$, HSV color space is firstly developed, and then extracte LTC histogram from each channels of image.

(1) For the H-channel, according to the LTC feature calculation process, calculate the 3×3 window corresponding LTC feature, and obtain matrix F_u F_l, where F_u is the upper pattern and F_l is the lower pattern in Fig. 2.

(2) According to Eq. (1), calculate the normalized histogram $H(i)$ of F_u and F_l, whereby $9 \times 2 = 18$-dimension classification feature is obtained.

$$H(i) = \frac{1}{M \times N} \sum_{x=0}^{M} \sum_{y=0}^{N} (F(x, y) = i), \tag{1}$$

where, upper or lower LBC Code $i = 0,1, ..., 8$. In order to improve the discrimination of the histogram component, better the detection rate, histogram component logarithmic transformation is made according to Eq. (2).

$$\log H(i) = \log_{10}(1 + H(i)). \tag{2}$$

(3) For the S-channel and V-channel repeat steps (1), (2), receive a total of $9 \times 2 \times 3 = 54$ dimensional feature.

2.3. Establish Classification Model

Select classifier SVM LIBSVM [12], wherein use RBF kernel function as the core function, RBF kernel has good performance in the emperiment, in the cross-validation process automatically find the optimal penalty factor C and kernel function parameter γ by using grid search method. Get classification features while adding PIM and PRCG Properties tag, labeled PIM (+1), PRCG(–1). Put classification feature and attribute labels into the classifier for training and classification, detect PRCG.

3. EXPERIMENTAL RESULTS AND ANALYSIS

3.1. Experiment Settings

Experimental hardware environment: 2.70 GHz, AMD Athlon (tm) 7750 processor, 2 GB memory; software environment: Opencv 2.3.1 + Microsoft Visual Studio 2010.

One thousand two hundred PIM and 1000 PRCG are selected in our experiment. Wherein 800 PIM and 200 PRCG from the Columbia University natural image library [13], and the remaining 400 PIM are collected by ourselves; 800 PRCG image is downloaded from well-known PRCG sites. Images of library are sized varies, storaged format JPEG, contained figures, landscapes, architecture, and so on.

To test the classification performance of the exacted feature, each experiment randomly selected from an image library 4/5 image (i.e., 960 PIM and 800 PRCG) as training samples, the remaining 1/5 (i.e., 240 PIM and 200 PRCG) are as test samples. Select 10 test results as the average classification performance evaluation, in order to reduce the impact random sample of results produced. PRCG correct detection rate (*TP*), PIM correct detection rate (*TN*) and the comprehensive correctly detection rate (*Accuracy*) of all test images are used to evaluate the performance of the algorithm.

$$Accuracy = \frac{m \times TP + n \times TN}{m + n}, \tag{3}$$

where m is the number of PRCG test images and n is the number of PIM test images.

3.2. Threshold Decision

LTC features threshold t is selected by experimental results. The classification performance comparison between different threshold t is shown in Fig. 5. It is shown that if t is set as 1, both PIM or PRCG can get the hightest performance. With t values increasing, detection performance begins to decline. Taking into account that it make no sense selecting large threshold value t, here the value of $t = 1$ is selected.

3.3. Color Space Evaluation

On the basis of the results, RGB, LAB, YCrCb, HSI, and HSV color space are used to do comparative tests, as shown in Fig. 6. Zheng [14] also showed that the recognition rate of HSV color space is 5% higher than the recognition rate of RGB color space. Consistently, the recognition rate of HSV color space is 1% higher than RGB in our experiment.

3.4. Comparative Analysis

The image rotation invariant LBP histogram feature extracted on YCrCb color space to detect PRCG and PIM [11], achieve good results. In terms of the

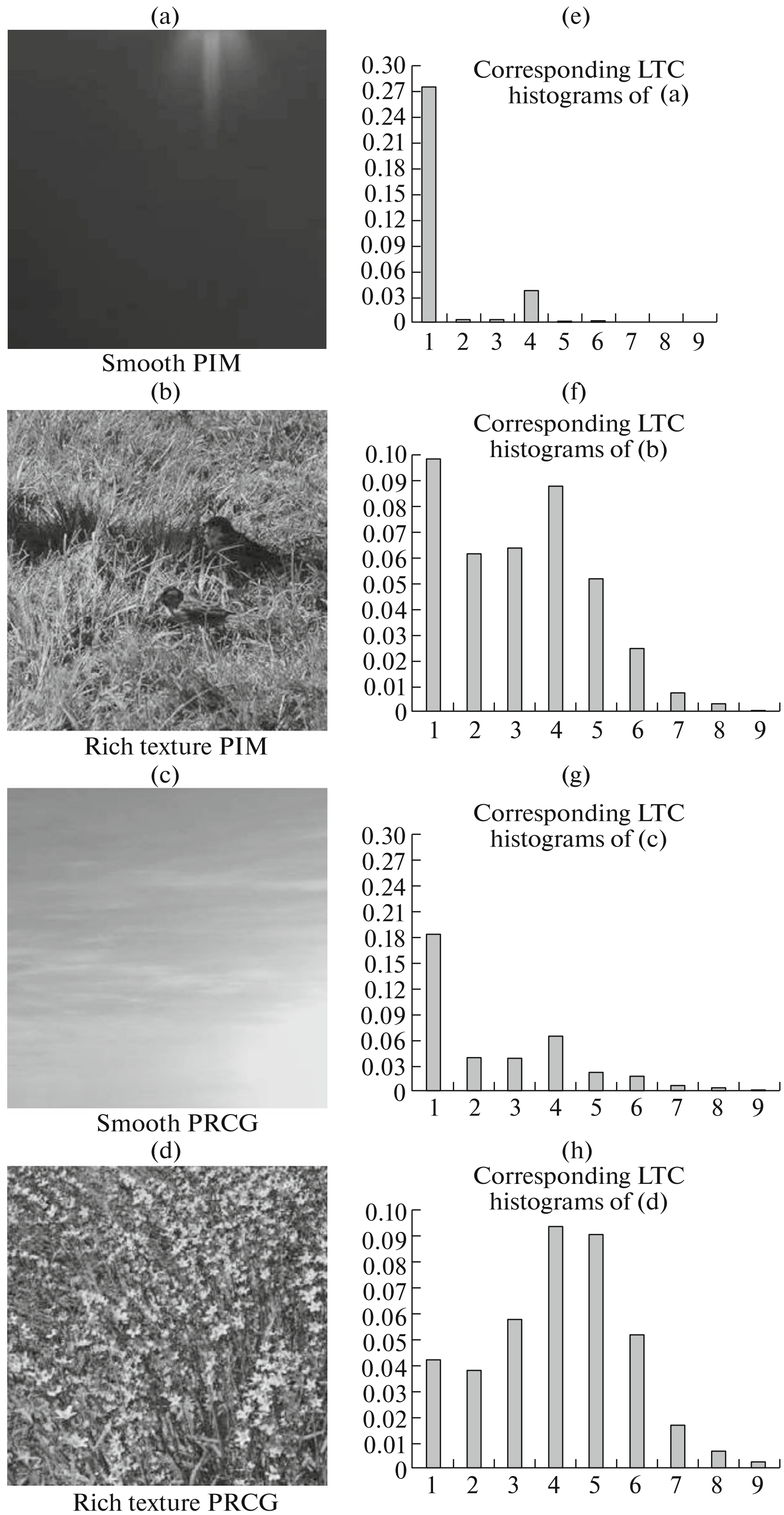

Fig. 3. Typical PIM and PRCG comparison LBC histogram.

detection rate, feature dimensions, and running time, the detailed comparative analysis of LBP, LBC-based implementation and our method (LTC) are shown in table.

It shows that counting mode can significantly reduce the amount of computation, while relatively small impact on the test results. The recognition rate

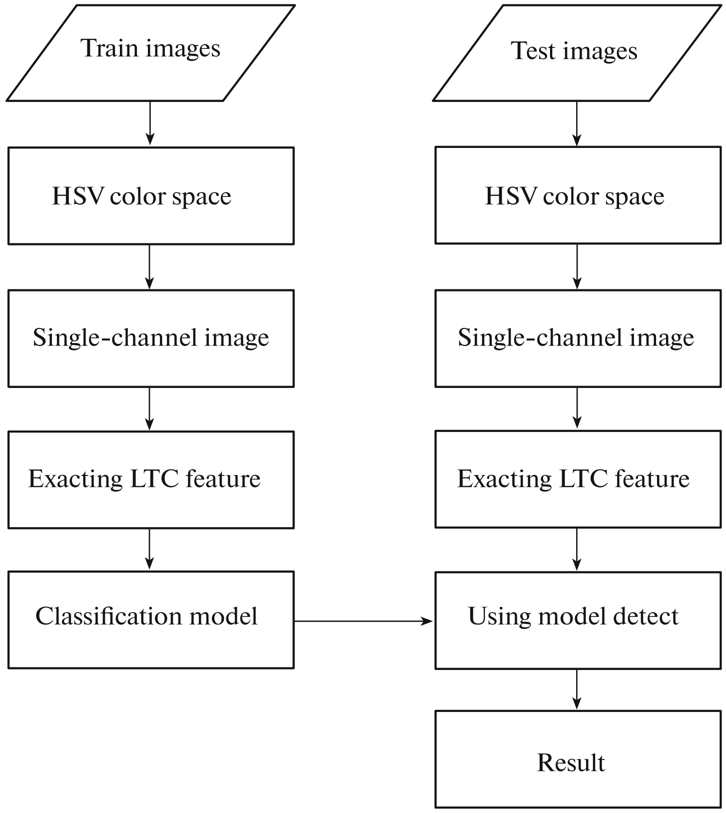

Fig. 4. The basic flowchart of the algorithm.

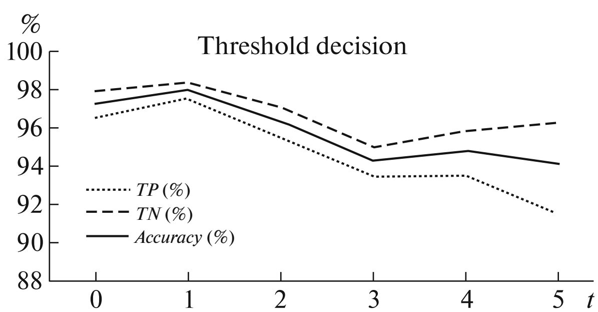

Fig. 5. Different values of Threshold *t* results comparison table.

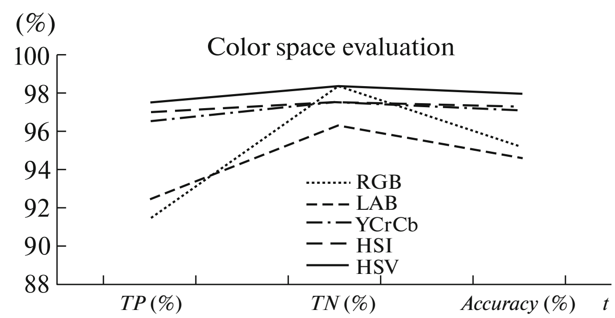

Fig. 6. Results of different color spaces.

of algorithm reaches 97.95%, which extracts LTC features in HSV color space, although slightly lower than LBP [11] detection rate. However, LTC features characteristic dimension has only 54 dimensions, significantly lower than the LBP [11] (236 dimensions), greatly speeding up the processing. In addition, the run time of LTC (image size 256 × 256) is reduced than LBP, which indicates that LTC is more suitable for PRCG and PIM image classification.

Results of different algorithm

Algorithm	*TP* (%)	*TN* (%)	*Accuracy* (%)	Dimensions	Run time (pic/ms)
LBP	98.50	97.92	98.18	236	170
LBC	96.00	97.92	97.05	27	149
LTC	97.50	98.33	97.95	54	149

4. CONCLUSION

To solve the problem that the excess high characteristic dimensions of the existing method of detecting PRCG using LBP, a novel method using the LTC is proposed. First, convert RGB color images to HSV color images from image library and then image isolated H, S, and V three single-channel images. Secondly, for each single-channel images, LTC normalized histograms are exacted and give 54-dimensional classification characteristic. Finally, use SVM classifier to train and classify, then detect PRCG and PIM. Experimental analysis shows that although the LTC detection rate slightly lower than the LBP detection rate, also have effectively implement the PRCG detection. In addition, the proposed method greatly reduces the characteristic dimension of classification features and the running time.

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TAN Da-Qi. Master degree candidate at the College of Computer Science and Technology, Jilin University. His study and research interests include image processing and pattern recognition, in particular, forgery and tampering detection.

Shen Xuan-Jing. Professor at the College of Computer Science and Technology, Jilin University. He received his Ph. D. degree from Harbin Institute of Technology in 1990. His research interest covers multimedia technology, computer image processing, intelligent measurement system, and optical-electronic hybrid system.

Qin Jun Ph. D. Candidate at Intelligent Control and Embedded Systems Laboratory, College of Computer Science and Technology, Jilin University. His research interest covers image processing and computer graphics.

Chen Hai-Peng. Associate professor at the College of Computer Science and Technology, Jilin University. His research interest covers image processing and pattern recognition.