A Novel Photographic and Computer Graphic Composites Detection Method

Zhenwei Chen
School of Computer Science and Software
Tianjin Polytechnic University
Tianjin, China
waitchen1988@gmail.com

Yongzhen Ke
School of Computer Science and Software
Tianjin Polytechnic University
Tianjin, China
keyongzhen@tjpu.edu.cn

***Abstract*— With the development of the rendering techniques, the visual difference between photographic images (PG) and computer graphics (CG) is becoming smaller. And the digital image forgery is not limited to the composite between photographic, splicing of computer graphics and photographic is also a problem to be resolved. To come up with this problem, in this paper we propose a novel hybrid classifier based on pattern noise statistics and histogram features. Experimental results show that proposed method is capable of improving the performance of the prior techniques. The proposed method also has a good performance on detection of local forgeries.**

Keywords-digital image forensics; computer graphics; pattern noise; histogram features

I. INTRODUCTION

Nowadays, computer graphic processing technology is more and more popular. So modern CG makes the images and videos look very fantastic and beautiful, just like the life in the movie Avatar which is hard to arrange in real world. Figure 1 shows some scenes in the movie Avatar. In the two scenes, the background is obtained from real world, but the people and the robots are formed by compute generated graphics. The composite technology brings us wonderful visual enjoyment. However, this technology may also be used to forge image for cheating others. Therefore, identifying CG and PG turns out to be an inevitable issue in both image forgery detection and a benchmark for rendering software.

Recently, researchers have come up with some effective methods aiming at distinguishing between PG and CG. Farid uses a statistical model based on first four order wavelet statistics to capture regularities inherent to photographic images [1]. A three level quadrature mirror filter (QMF) is computed, and the numbers of features is 72D per color channel, so 216D features is formed in total considering the three color channels. The prior work [2] gives an image model based on geometry, the proposed model revealed certain physical differences between the two categories, such as the gamma correction in PG and sharp structures in CG. The 192D geometry features are extracted from each image. In [3], the authors propose that sensor pattern noise can be served as unique identification fingerprint of the images. The pattern noise can be obtained from images using a denoising filter. In [4], the paper pointed that image acquisition in a digital camera is fundamentally different from the generative algorithm deployed by computer generated imagery. Pattern noise introduced by different digital cameras may have common properties, but this common characteristic will not be present in computer graphics. So the pattern noise can be used to identify the differences between CG and PG.

There are many forensic techniques for identifying PG and CG, but now we are facing a new problem that the composition of PG and CG is also a challenge for the authenticity of digital images. i.e., objects created by computer graphics software are inserted in natural images, and vice versa. So we can’t simply say the image is PG or CG, but we may find out that some small blocks in the image are CGs and others are PGs. we need more efficient classifier that can work on small blocks. In [5], Conotter et al develop a novel hybrid classifier to improve performances of existing method and to detect local forgeries. Their method is based on wavelet transform domain features as described in [1] and sophisticated pattern noise statistics. The total dimension of features is as many as 228D.

In this Paper, in order to further improve the performance of the classifier and decrease the dimension of features, we take advantage of the histogram features and pattern noise statistics features to perform the feature sets. Using new feature sets, our method can get a higher accuracy rate with only 68D features.

This paper is organized as follows. The proposed method is described in Section 2, experimental results is discussed in section 3. Finally, conclusion is drawn in section 4.

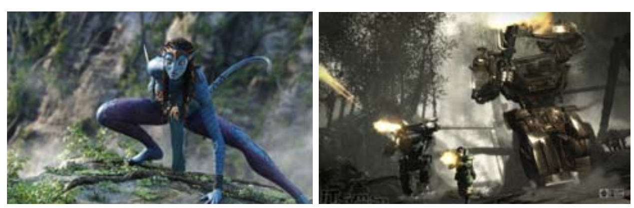

Figure 1. Examples of composited images

II. PROPOSED METHOD

In order to reduce the dimension of the features without losing the accuracy, we propose a hybrid method by merging noise based features and histogram features [6]. And then images are classified by using least squares support vector machine (LSSVM).

A. Sensor Pattern Noise

Sensor pattern noise is caused by imperfection during the sensor manufacturing process and different sensitivity of pixels to light due to inhomogeneity for silicon wafers. For a given digital camera, the sensor pattern noise remains approximately unchanged in each image [3], so sensor pattern noise has been widely used in source identification. Due to the differences in image generated process. As described in [4], the model of extracting the Sensor Pattern noise from an image is:

$$Noise = I - F\left(I\right) \qquad (1)$$

where F is a denoising function. The denoising filter used in [3, 4] is wavelet denoising filter, but wavelet denoising filter performs poorly for textures and smooth transitions. The performance of the filter has big affect on experimental results, in order to improve denoising performance, we employ a novel sophisticated denoising filter, namely sparse 3D transform domain collaborative filtering proposed by Dabov et al in [8]. This denoising strategy is based on an enhanced sparse representation in transform domain. The main algorithm is realized using three steps:

1) *grouping similar 2D image blocks into 3D data arrays.*
2) *Shrink the transform spectrum.*
3) *Inverse 3D transform.*

This denoising strategy not only reveals details shared by grouped blocks, but also retains the essential unique characteristics of each individual blocks. After we get the residual images by the denoising filter, we can compute first four order statistical features from each color channel, so 12D features are extracted from all three color channels of each residual image.

B. Histogram Features

Most statistical based methods usually compute statistical quantities (e.g., mean, variation, skewness and kurtosis [1]) to extract features. However, the histograms themselves can be directly used as features [7]. For a given image I , its first order difference image is defined as I_i , where i denotes four directions (horizontal, vertical, diagonal, anti-diagonal) of difference image. So the first order difference images can be computed as follow:

$$I_i = I * f_i \ , \ i \in \{h, v, d, a\} \qquad (2)$$

where f_i are convolution kernels in four directions.

$$f_h = (1, -1),\ f_v = \begin{pmatrix} 1 \\ -1 \end{pmatrix},\ f_d = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix},\ f_a = \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix} \qquad (3)$$

A similar process can be done for second-order difference images:

$$I_{i,j} = I * f_i * f_j \ , i, j \in \{h, v, d, a\} \ . \qquad (4)$$

Notice that $I_{i,j} = I_{j,i}$, so we can get 14 difference images in total. Then we compute the normalized histogram H_i :

$$H_i\left(n\right) = \frac{\#\left\{\left(x, y\right) : I_i\left(x, y\right) = n\right\}}{N}, \quad -255 \le n \le 255 \ .(5)$$

where N is the total number of pixels in difference image I_i , and # denotes the cardinal number of a set. For each difference images, we can get following features:

$$H\left(0\right), \frac{H\left(1\right) + H\left(-1\right)}{2}, \ldots, \frac{H\left(k\right) + H\left(-k\right)}{2} \qquad (6)$$

Thus we can get 14(1+k) histogram features. The features extracting process is shown in Figure 2.

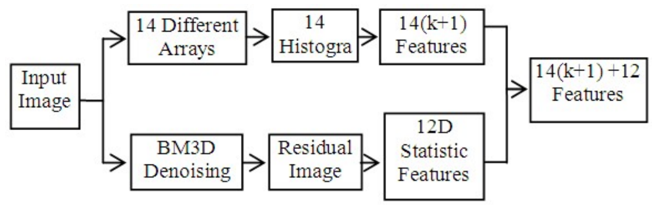

Figure 2. Features extraction from each input image

C. Local Forgeries Detection

With the development of rendering technology, we can get photorealistic computer generated graphics easily. Furth more, we can splice compute generated graphics into photographic images, and vice visa. So the composition of PG and CG is a new challenge for the authenticity of digital images. In order to automatically detect the local forgeries, we propose a PG and CG composites detection mechanism based on our proposed classification method. In this mechanism, firstly, we must train the LSSVM classifier, we use the images in our database as the training set, and extract proposed features from every image, the features will be sent to our LSSVM classifier, and then we can get a training model. Secondly, each spliced images in testing set is divided into overlapping blocks with size of n*n, as a result, for an M*N pixels image, we can get (M-n)*(N-n) blocks, and then extract features had described above from each block. Finally, those features from blocks are sent to the trained LSSVM, these blocks will be divided into two categories. According to the categories of blocks, we can mark these blocks with different colors. Therefore, we can find out the forgery area. The detection process is shown in Figure 3.

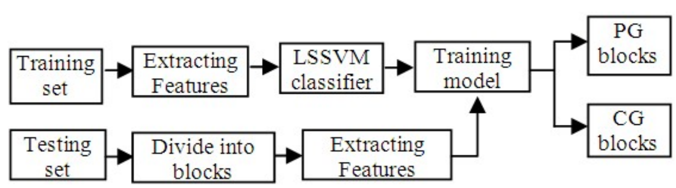

Figure 3. Composite detection method

III. EXPERMNET RESULT

A. Image Dataset

In the experiment, we used 800 photographic images in the Columbia Image Dataset [8] and 800 computer graphics (download from irtc.org) with different level of photorealism. All images are colored, compressed JPEG, and with different size. The scenes of the images have a wide rage including indoor and outdoor scenes with landscape, persons, and objects. Figure 4 shows some examples of computer graphics and Figure 5 shows some examples of photographic images in our image Dataset.

Figure 4. Some examples of computer graphics

Figure 5. Some examples of photographic images

B. Proposed Method Performances

The Least Squares Support Vector machine (LSSVM) classifier with RBF kernel was employed in the experiment. We used the "grid-search" method to find the optimal parameters σ and γ of RBF kernel. To train the LSSVM classifier, we randomly selected half of the images (400 PGs and 400 CGs) as training set, and the rest of the images (400 PGs and 400 CGs) are used as testing set. So there is no intersection between the training set and testing set

In the experiments, there are 14(k+1) histogram features, we set k =3 to balance detection performance and feature dimension, so 68D features are formed by 56D histogram features and 12 pattern noise features.

Experiments show that the proposed classifier has an 88.25% classification accuracy which is better than the Histogram based method's 86.25%. From the experimental results, we can see that the approach by combination of such features is reasonable. Experimental results are given in Table 1.

TABLE I. ACCURACY PERFORMANCES OF OUR ALGORITHM

Noise based	Histogram based	Hybrid
66.25%	86.25%	88.25%

In addition, we made comparisons with some other prior works, the results in table 2 show that our method outperforms all methods in [1, 3, 5], and the dimensions of features in our method are fewest. The experiments show the effectiveness of our hybrid classifier.

TABLE II. COMPARISONS BETWEEN THE PROPOSED METHOD AND PREVIOUS WORKS

Noise based	Feature Dimension	Accuracy
[1]	216D	82.5%
[2]	192D	83.5%
[5]	228D	85.3%
Proposed	68D	88.25%

C. Detection of local forgeries

In the above description, the proposed method based on pattern noise statistics and histogram features shows excellent characteristics in the distinction between PG and CG. In order to automatically detect the local forgeries, we used proposed classifier to detect composite images.

Some examples of forgery images are shown in Figure 6, (a) and (b) are two images spliced by us. The images are divided into blocks with size of 128*128 pixels, and the forgery portion has a bigger size. For each block, we extract 68D features, and then the features are sent to the LSSVM classifier, the parameters of RBF kernel are set to $\alpha = 15 \quad \gamma = 20$. If the test result of one block is CG, we then mark the central pixel of the block with white color. Figure 6 (b) and (d) are the test results. White areas represent CG areas detected by our classifier. The results show that our classifier has good performance on detecting local forgeries.

(a) (b)

(c) (d)

Figure 6. Some examples of local forgeries detection

IV. CONCLUTIONS

A novel hybrid classifier based on pattern noise statistics and histogram features has been presented in this paper. Compared with prior methods, not only the dimension of features is smaller, but the accuracy rate is higher. Experimental results show the effectiveness of the approach.

When come up with the photographic images and Compute graphics composites problems, the proposed method also has a good performance on detection of local forgeries.

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