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Image Splicing Detection Using Illuminant Color Inconsistency

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Abstract—**Splicing operation may introduce inconsistencies in many features. In the proposed method illuminant color inconsistency is used to detect image splicing. A given color image is divided into many overlapping blocks. Then a classifier is used to adaptively select illuminant estimation algorithm based on block content. Illuminant color is estimated on each block, and the difference between the estimation and reference illuminant color is measured. If the difference is larger than a threshold, the corresponding block is labeled as spliced block. Experiments show effectiveness of the method.**

Keywords-splicing detection; illuminant inconsistency; illuminant estimation;

I. INTRODUCTION

Nowadays digital image has been widely used in many fields. With many powerful image processing tools, non-professional users can easily modify the image content and not leave visible traces. As a consequence, people are no longer convinced of image authenticity as before. Effective methods are needed urgently to detect image forgery.

As a commonly used step in image tampering, image splicing has received much attention in recent years. Many researchers used statistical inconsistency to detect image splicing. Hilbert-Huang transform and wavelet decomposition[1], statistical moments and Markov transition probability matrix [2], and statistic features of 2-D phase congruency[3] were used to detect spliced image. Ng used bicoherence as well as other features to detect the high order correlation introduced by splicing[4]. Furthermore, the inconsistency in the physical attributes of camera among different image areas can also be used to detect image splicing. Hsu and Chang detected image splicing based on estimation of the camera response function, consistency checking and image segmentation[5]. Besides, discrepancies in motion blur[6] and inconsistencies in light source direction[7] were employed to detect spliced image.

Illuminant inconsistency between spliced and authentic area is an important feature in splicing detection. Most of the existing method can identify a given image as authentic or spliced using classification approach, and did not adequately locate the spliced area.

In this paper, we introduce a new approach to detect image splicing and locate splicing area by exploiting illuminant color inconsistencies. The rest of the paper is organized as follows. In Section 2, we introduce scene illumination estimation methods. In Section 3, the proposed method based on illumination inconsistency is introduced. Section 4 presents experimental results and discussion. Section 5 concludes the paper.

II. SCENE ILLUMINATION ESTIMATION

The image values, $f=(R,G,B)^T$, for a Lambertian surface depend on the light source $e(\lambda)$, where λ is the wavelength, the surface reflectance $s(X, \lambda)$ of the spatial location X and the camera sensitivity function $c(\lambda)$

$$f(X) = \int_w e(\lambda)s(X,\lambda)c(\lambda)d\lambda \qquad (1)$$

Where w is the visible spectrum. It assumed that the scene is illuminated by a single light source. The goal of illuminant estimation algorithm is to estimate the light source color $e(\lambda)$, or its projection on the RGB-kernels

$$e=(R_e, G_e, B_e)^T = \int_w e(\lambda)c(\lambda)d\lambda \qquad (2)$$

Both of $e(\lambda)$ and $c(\lambda)$ are unknown, so the task of color constancy is not attainable without further assumptions.

Recently illumination estimation has been a hot topic of color constancy field. The existing approaches can be divided into two types of algorithms. The first type of algorithms is physical-based methods. It assumes that the spectral reflectance distribution of the specular reflection component is similar to the spectral energy distribution of the incident light. The representative method is the dichromatic reflection model. The second type is based on low-level image features. The main methods are Grey-World, Grey-Shadow and Grey-Edge [10]. For instance, the Grey-World algorithm assumes that the average color in a scene taken under a neutral light source is achromatic, while the Grey-Edge algorithm assumes that the average edge is achromatic.

III. PROPOSED APPROCH

In the proposed method, a color image is first divided into many overlapping blocks. Illuminant color is estimated

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on each block, and the difference between the estimation and reference illuminant color is measured. If the difference is larger than a threshold, the corresponding block is labeled as spliced block. Considering the impact of image content on the illumination color estimation, a maximum likelihood classifier is used to adaptively select illuminant estimation algorithm.

A. Illuminant color estimation

In order to estimate the light source color from the low level image features, we use three classical illuminant color estimation algorithms in this paper. These algorithms including Grey-Shadow, first-order Grey-Edge and second-order Grey-Edge algorithm, which can be incorporated into the following framework[10]:

$$e(n, p, \sigma) = \frac{1}{k}\left(\iint \left| \nabla^n f_\sigma(x, y) \right|^p dxdy \right)^{1/p} \qquad (3)$$

Where n is the order of the derivative, p is the Minkowski norm. Further, the derivative is defined as convolution of the image with the derivative of a Gaussian filter with scale parameter σ. The Grey-Shadow algorithm, first-order Grey-Edge and second-order Grey-Edge is equivalent to $e(0,p,0)$, $e(1,p,\sigma)$ and $e(2,p,\sigma)$ respectively.

The performance of illuminant estimation algorithm is largely dependent on the distribution of colors and color edges in an image. For example, the Grey-Shadow algorithm performs better than higher-order methods on images with only little texture, and higher-order methods need more edge information for an accurate illuminant estimation[11].

To select the most appropriate illuminant estimation algorithm for a specific image block, we use maximum likelihood classifier proposed by Gijsenij and Gevers to achieve adaptive algorithm selection[11].

First, the distribution of color and edges in an image block is modeled using the two parameter integrated Weibull distribution,

$$w(x) = C \exp\left(-\frac{1}{\gamma}\left|\frac{x}{\beta}\right|^\gamma\right) \qquad (4)$$

Where x is the edge response in a single color channel to the Gaussian derivative filter, C is a normalized constant. β indicates the contrast of the image, γ represents image texture.

Then a maximum likelihood classifier based on mixture of Gaussian (MoG) is used to select the proper illuminant color estimation algorithm. Weibull parameterization is related to the image attributes to which the candidate algorithms are sensitive. The MoG-classifier is used to learn the correlation and weighting between the Weibull-parameters (grain size and contrast) and this image attributes (number of edges and amount of texture and SNR). The output of the classifier is the selection of the best performing method.

Because R, G, and B channels are highly correlated, the image is first transformed to an opponent color space before computing Weibull parameters:

$$O_1 = \frac{R-G}{\sqrt{2}}, \quad O_2 = \frac{R+G-2B}{\sqrt{6}}, \quad O_3 = \frac{R+G+B}{\sqrt{3}}. \qquad (5)$$

B. Illuminant color inconsistancy measure

After the color of the light source is estimated for every block, we compare it to the ground truth. The angular error between the estimated and real illumination is defined as

$$e_{angle} = acos\left(\frac{I_1 \bullet I_2}{\|I_1\| \bullet \|I_2\|}\right) \qquad (6)$$

where I_1 is the block based illuminant estimation, I_2 is the real illumination, and a is . If the angular error e_{angle} is larger than a specific threshold, the corresponding block is labeled as spliced.

However, the real scene illuminant color is generally unknown in empirical splicing detection application. So we choose some reference blocks and estimate its illumination as the approximation of real illuminant. Then we compute the angle error and detect the spliced block corresponding to each illuminant approximation. The intersection of spliced blocks based on different approximation is computed as the final detection result

IV. EXPERIMENTS

We use the image database presented by Ciurea and Funt[12] to ascertain proper image block size and train the classifier. Then, the CASIA Image Tempering Detection Evaluation Database[13] is used to determine the appropriate angle threshold β_0, which is used to detect spliced image and localize the forged block.

A. Block size selection

Most of these illumination estimation algorithms deal with the entire scene globally for the recovery of a single illumination color. To achieve splicing detection and location, we estimate local illuminant color based on image block. Table1 shows the average angle error between the real illuminant color and block estimation using 100 images from image database presented by Ciurea and Funt[12]. It can be easily seen that the angle error decreases when the block size increases. On the other hand, big block may decrease the location accuracy. Therefore we use 30×30 block in the following experiments.

Table 1 different block sizes for angle error

Block size	Angle error
10×10	20.81
20×20	11.93
30×30	7.07
40×40	5.67
50×50	4.92
60×60	4.41
70×70	4.12
80×80	3.53

We use the image database presented by Ciurea and Funt[12] that includes the true illuminant color for all images. We randomly select 500 outdoor images to train our classifier and use other 500 outdoor images to test the learned classifier. The accuracy of illuminant algorithm self-adaptive selection reaches 94%.

B. Angle error threshold selection

Fig. 1 shows the inconsistency between authentic and spliced blocks. Then we randomly select 100 spliced images. Two authentic blocks and one spliced block are chosen in every image. Using the adaptively selected algorithm, the illuminant color is estimated for each block and the angle errors are computed between authentic blocks, authentic and spliced block. The results are shown in Fig. 2.

Corresponding to an image index at ***x*-axis** in Fig. 2， the red circle represents the angle error between the authentic and the spliced block in a forged image, and the blue square represents the angle error among the authentic blocks in the same image. If the threshold of angle error is set to 7, the detection accuracy is about 75%

(a) Authentic image (b) Spliced image

Figure 1 (a). Angle errors among authentic blocks are 2.71, 2.68 and 0.56. (b). Angle error between authentic blocks is 3.47, and angle errors between authentic block and spliced block are 8.20 and 9.91.

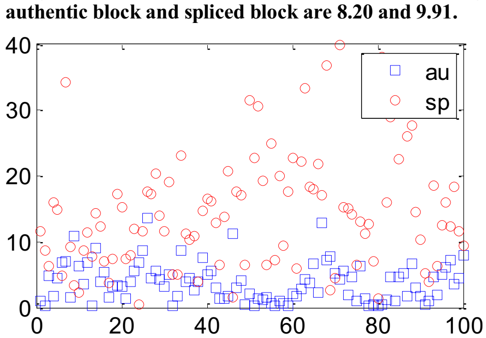

Figure 2 The angle threshold: *x*-axis represents different image index, *y*-axis represents angle error among image blocks.

C. Splicing detection

The CASIA Image Tempering Detection Evaluation Database[13] is used in splicing detection. Fig.3 shows the impact of reference block choosing. Nonetheless, the detection results according to three different reference illuminant show consistency. We have also tested the proposed algorithm on many forgery images spliced with contents from another image and obtained satisfactory results, some being shown in Fig.4.

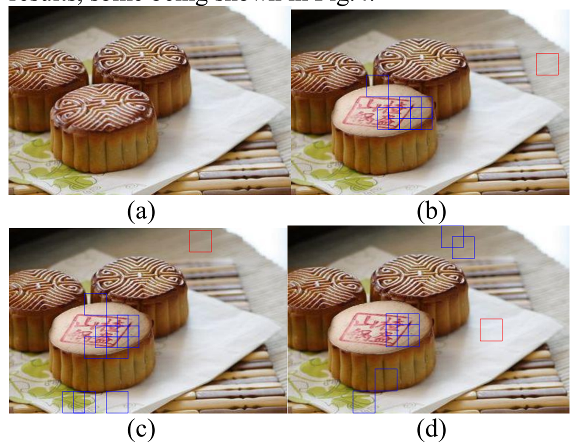

Figure 3 The red rectangle represents reference block. The blue rectangles are blocks with estimation error lager than a threshold. (a) is an authentic image.(b),(c),(d) are the detection results.

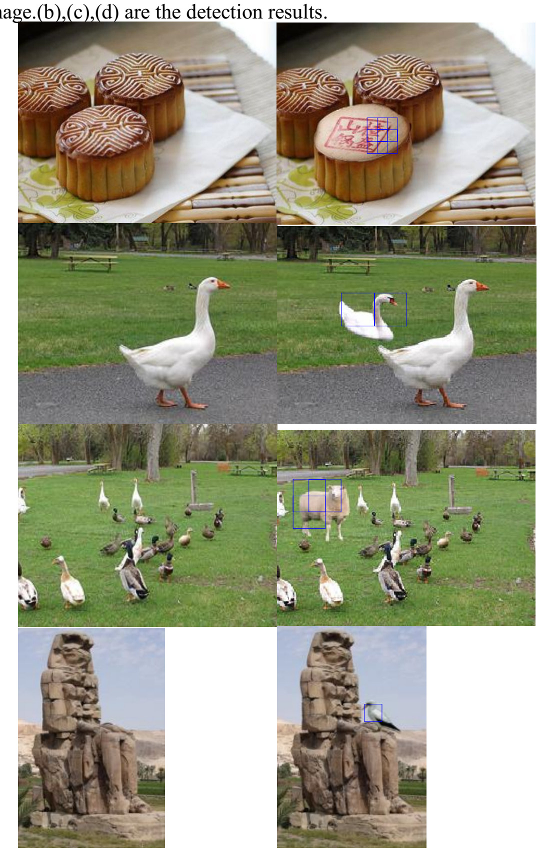

Figure 4 The final splicing detection results. The left row are authentic images, the right row are detection results of the spliced images. The blue rectangle represents spliced area detected by the proposed method.

V. CONCLUSIONS

Splicing operation often disturbs the consistency of image local illuminant. In this paper we present a method to detect image splicing and locate the spliced area using illuminant color inconsistency. The illuminant color is estimated based on image blocks. Then the estimation error of each block is calculated by comparing the estimates with the reference illuminant color. Experiment results show the effectiveness of the proposed method. Automatic selection of reference block and the algorithm applicability to indoor images will be discussed in our future work.

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