

Identifying Image Composites by Detecting Discrepancies in Defocus and Motion Blur

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Abstract—Image manipulation has become commonplace in today's social context. One of the most common types of image forgeries is image compositing. In recent years, researchers have proposed various methods for detecting such splicing. Most prior approaches to detecting blur post-processing operation suffer from their inability to identify the spliced region when the background region contained nature blur. In this study, we propose a novel algorithm of detecting splicing in blurred images. We use blur parameters estimation through the cepstrum characteristics of blurred images in order to restore the spliced region and the rest of the image. We also develop a new measure to assist in inconsistent region segmentation in restored images that contain large amounts of ringing effect. Experimental results show efficacy of the proposed method even if the images to be tested have been noised with different levels. Compared with other existing algorithms, the proposed method has better robustness against gaussian noise.

Index Terms—Image forgery detection, Photo composites, Blur estimation, Image cepstrum

I. INTRODUCTION

Tampering images has become extremely easy due to the easy accessibility of advanced image editing software and powerful computing hardware. Various types of forgeries can be created and in recent years, image forgery detection using passive techniques has become a hot area of research [1], [2].

One of the most common types of image forgeries is the image compositing, where a region from one part of an image is copied and pasted onto another part of different images, thereby concealing the image content in the latter region. Such concealment can be used to hide an undesired object or increase the number of objects apparently present in the image. In recent years, researchers have proposed various methods for detecting such composite and spliced images. These include techniques for resampling artifacts [3]; JPEG compression estimations [4]; color filter-array aberrations [5]; chromatic aberrations [6]; disturbances of a camera's sensor noise pattern [7]; camera response functions [8]; and lighting inconsistencies [9]. Many of these

techniques have an implicit assumption that the image has not undergone any post-processing. With the appearance of sophisticated photo manipulation software, such an assumption is unlikely to hold for most believable forgeries. Therefore, significant research has gone into circumventing postprocessing of images, such as blurring. Some researchers have proposed various methods for detecting this image forgeries using local [10] or edge [11] blur estimates.

It is shown in Fig.1 that the background region contains nature blur. In such case, the big issue consists in detecting efficiently the spliced region that has blur introduced. Introducing blur region into a spliced object, in general, depends on the perception of the person creating the forgery and hence, is unlikely to be completely consistent with the blur in the rest of the image. Researchers use this fact to present a solution to this tampering detection problem. Some techniques [12], [13] use discrepancies in defocus blur to discover forgeries. Others [14], [15] use motion blur estimation to detect image forgeries. Each of the methods mentioned above are limited to handle merely one kind of spliced blurred image.

There are two common types of blurs (defocus or motion) for most camera systems. According to the best of our knowledge, none of the existing works is suitable for both spliced defocus blurred image and spliced motion blurred image. In this paper, we use blur parameters estimation through the cepstrum characteristics of forged images in order to restore the spliced and the background regions. The faked regions could be detected thanks to the inconsistent ringing effect in the restored image. Experimental results show that our technique provides good segmentation of regions with inconsistent blurs and is suitable for both defocus blur and motion blur.



Figure 1. Forged image

II. DEFOCUS AND MOTION BLUR ESTIMATION

There are two common types of blurs for most camera systems. One is the defocus blur (such as Fig. 2(a)) due to the optical system's defocus phenomenon and the other is the motion blur (such as Fig. 2(c)) due to the relative movement between the objectives and the camera. For a blurred image, the blurring process is modeled as the convolution of a sharp image with a blurring kernel:

$$I(i, j) = (F * H)(i, j) + N(i, j) \quad (1)$$

where $I(i, j)$ is the blurred image, $F(i, j)$ is the sharp image, $H(i, j)$ is the blurring kernel, and $N(i, j)$ is the noise present. i and j are the pixel coordinates.

Taking the Fourier transform of (1)

$$\hat{I} = \hat{F}\hat{H} + \hat{N} \quad (2)$$

where $\hat{I}$, $\hat{F}$, $\hat{H}$ and $\hat{N}$ represent the Fourier transform of I , F , H and N respectively.

A. defocus blur model

For a typical defocus blur, the blurring kernel H_d can be modeled as

$$H_d(i, j) = \begin{cases} \frac{1}{\pi R^2} & \sqrt{i^2 + j^2} \leq R \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where the continuous-time H_d is a circular symmetric cylinder function. And its Fourier transform $\hat{H}_d$ is expressed:

$$\hat{H}_d(\omega_1, \omega_2) = 2\pi R \frac{J_1(R\sqrt{\omega_1^2 + \omega_2^2})}{\sqrt{\omega_1^2 + \omega_2^2}} \quad (4)$$

where, $J_1(\cdot)$ denotes the first order of first kind Bessel function. $\hat{H}_d(\cdot, \cdot)$ resembles the shape of two-dimensional $\sin C(\cdot, \cdot)$, as shown in Fig. 2(b).

B. motion blur model

For a horizontal uniform velocity motion blur, the continuous-time H_m is described as follow as:

$$H_m(i, j) \Big|_{j=0} = \begin{cases} \frac{1}{d} & -\frac{d}{2} \leq i \leq \frac{d}{2} \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where d is the length of the kernel. Note that a directional blurring kernel can be formulated by rotating H_m by θ degrees about the x-axis. Taking the Fourier transform of (5)

$$\hat{H}_m(\omega_1, \omega_2) \Big|_{\omega_2=0} = \frac{2 \sin(\omega_1 d/2)}{\omega_1 d} \quad (6)$$

where $\hat{H}_m(\cdot, \cdot)$ has a series of parallel gratings, as shown in Fig. 2(d).

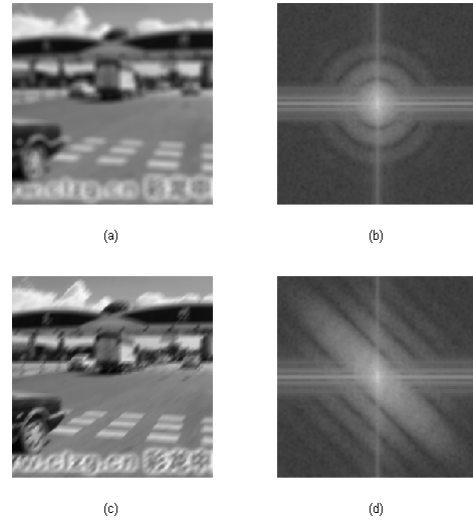


Figure 2. Blurred images and DFT s. (a) Defocus blurred image ($R=5$). (b) DFT for (a). (c) Motion blurred image ($d=10$, $\theta=45^\circ$). (d) DFT for (c).

III. PROPOSED FORGERY DETECTION METHOD

We propose a method to detect blurred image forgeries using blind image restoration. Blur parameters are first estimated from the cepstrum of the given image, as defined in Section III-A. Our technique then restores the image based on these parameters, segmenting the regions with inconsistent ringing effect. The proposed method is especially useful for exposing the possible forgeries in blurred regions, such as spliced objects with artificial blur perceptually close to the background blur, making the inconsistency in blur difficult to detect.

A. Blur Parameter Estimates

In general, we address compositing in a nature-blurred (such as defocus or motion blur) image, with the artificial blur introduced in the spliced part similar to the background blur, so that the inconsistency is difficult to perceive visually. But, the spectrum of the forged images still have the shape of two-dimensional

$\sin c(\cdot, \cdot)$, as shown in Fig. 3. Instead of employing the spectrum characteristics directly, we use a variant of the widely recognized cepstral method [16] in order to estimate defocus and motion blur. Such an approach has been shown to be more robust to noise than just using the spectrum of the image.

Omitting the noise $\hat{N}$, the cepstrum of the blurred image I is defined as

$$C(I) = \log |\hat{I}| \quad (7)$$

Notice that the cepstrum is additive under convolution, that is,

$$\begin{aligned} C(I) &= \log |\widehat{F * H}| = \log |\hat{F}| + \log |\hat{H}| \\ &= C(F) + C(H) \end{aligned} \quad (8)$$

which has a circular symmetric distribution or some symmetric spike pairs along the direction of motion, as shown in Fig. 4. For a spliced defocus-blurred image, the first centered ring in the cepstrum shown in Fig. 4 (a) usually has the radius $r_C = 2R - 1$ [16]. Here, a peak detection method for the radius r_C is proposed in this paper. The proposed approach firstly extracts the diagonal line of the cepstrum image, and then detects the peaks along the direction of the diagonal line. At last, the radius r_C is detected by the distance between the middle point and the maximum peak, as shown in Fig. 5 (a). The parameter r_C is obtained with $r_C = 9$ from Fig. 5(a). Further, the defocus blur radius R can be estimated with $R = 5$ for the forged image in Fig. 3 (a). For a spliced motion-blurred image, instead of directly detecting the cepstral peaks, the Radon transform, which is widely used for detecting straight lines in noisy images, is used. Fig. 5 (b) gives the peak curve image, where shows the maximum value of the Radon-transformed images in each column. As can be seen, the peak point of peak curve images just refers to the motion direction θ , here, $\theta = 45^\circ$ for the forged image in Fig. 3 (c). The second parameter of motion blur is the motion length d , which can be obtained by the distance between the half of two bright points, as shown in Fig. 4 (b). The proposed approach firstly rotates cepstrum image by an angle of θ using the estimated motion direction, and then detects the peaks along the direction of the middle column. At last, the parameter d is detected by the distance between the center point and its nearest spike, as shown in Fig. 5 (c). Here, $d = 9$ for the forged image in Fig. 3 (c).

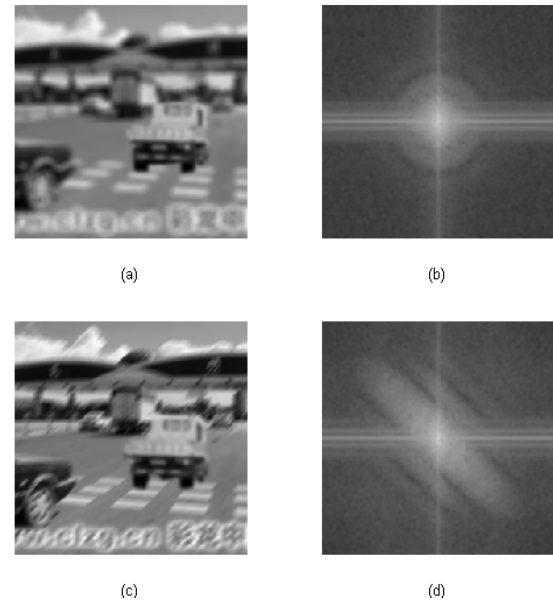


Figure 3. Forged images and DFT s. (a) Spliced image for Fig. 2(a). (b) DFT for (a). (c) Spliced image for Fig. 2(c). (d) DFT for (c).

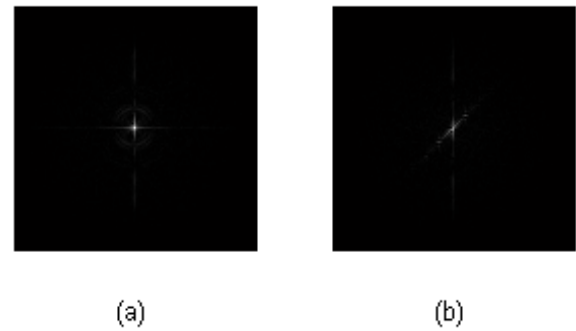


Figure 4. Comparison of cepstrums. (a) and (b) are the cepstrums $C(I)$ of forged images in Fig. 3 (a) and (c) respectively.

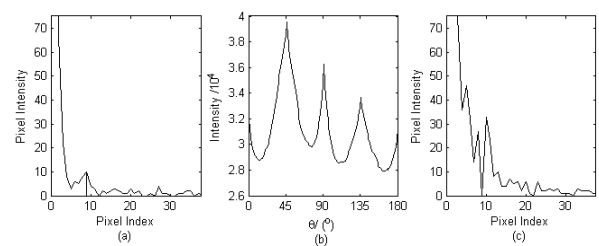


Figure 5. Estimated the blur parameters for Fig. 4. (a) is half the diagonal line of cepstrum images in Fig. 4 (a). (b) is the peak curve of Radon-transformed image for Fig. 3(d). (c) is half the middle column of rotated image for Fig. 4(b).

B. Blind Image Restores

The blurring kernels of the spliced blurred image are constructed by estimating the blur parameters in section III-A. Then with the constructed blurring kernels, the forged images are restored by performing the R-L blind restoration method.

In this section, we use classical R-L blind restoration method to restore the forged images (such as Fig. 3(a) and (c)), where the iteration times is 20, obtaining the restored images which are shown in Fig. 6. From Fig. 6, the spliced regions suffer serious ringing effect due to

inconsistent blur parameters in the forged region and background region. Hence, the spliced regions can be accurately segmented by measuring the ringing effect in the restored image.



Figure 6. Restored images. (a) Restored image for Fig. 3(a). (b) Restored image for Fig. 3(c)

C. Ringing Effect Measures

For restored images in which certain regions appear to have large amounts ringing effect, we propose using the sum of absolute pixel gradient, generating a new *ringing effect measure (REM)* method. Firstly, the restored images $I_r(i, j)$, such as Fig. 6, are divided into $k \times k$ sub-blocks as

$$b_{x,y}(i, j) = I_r(i, j)(1 + k(x-1) : kx, 1 + k(y-1) : ky) \quad (9)$$

where $b_{x,y}(i, j)$ denotes sub-block with $x = y = 1, 2, \dots, \left\lfloor \frac{M}{k} \right\rfloor$. Secondly, the REM of the row or column in $b_{x,y}$ is defined:

$$REM_{row} = \frac{1}{k} \sum_{i,j=1}^k |b_{x,y}(i, j+1) - b_{x,y}(i, j)| \quad (10)$$

$$REM_{col} = \frac{1}{k} \sum_{i,j=1}^k |b_{x,y}(i+1, j) - b_{x,y}(i, j)| \quad (11)$$

Lastly, the larger one of REM_{row} and REM_{col} is used to represent the ringing effect of the sub-block.

$$REM(b_{x,y}) = \max(REM_{row}, REM_{col}) \quad (12)$$

So, the spliced regions are accurately segmented by classifying the ringing effect of each sub-block.

IV. RESULTS AND COMPARISONS

In the first experiment, simulations are performed to show efficacy of the proposed method. We created a database of 12 forged images, shown in Fig. 7, containing defocus blur and motion blur. The original images were obtained from the popular photo-sharing website. We spliced different objects into the blurred backgrounds of the images and applied visually similar artificial blurs, using the Photoshop image editor. To demonstrate validity of the proposed method, an example of the detection for spliced regions is shown in Fig. 8. In Fig. 8, column (a) gives 3 forged images from the database, where the spliced regions undergone Gaussian blur, Box blur and Shape blur (from up to down),

respectively. column (b) in each figure shows the corresponding cepstrum image of column (a). The blur parameters are estimated from the cepstrum of the forged images, as defined in section III-A. Column (c) of each figure shows the restored results. The spliced regions are accurately detected by performing REM method defined in section III-C, as shown in column (d). It is observed that the proposed method can correctly identify fake objects with inconsistent blur parameters in nature-blurred images even if the spliced regions undergo various postprocessing operations.



Figure 7. Images in our database.

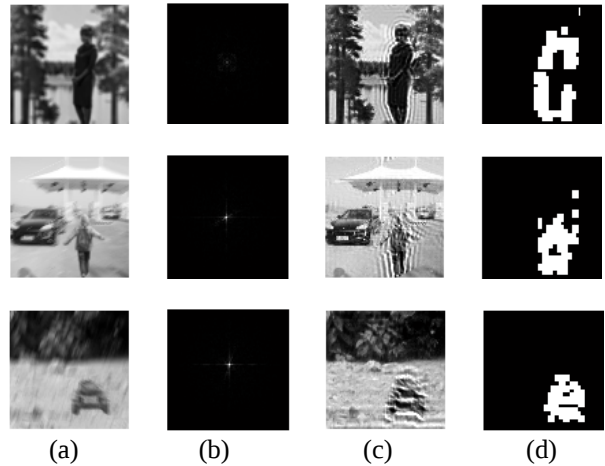


Figure 8. Detection for spliced blurred regions. (a) Spliced blurred images. (b) C(I) s for (a). (c) Restored images. (d). Detection using REM s

In the second experiment, the proposed algorithm is tested on several forged images with different noise levels. The purpose of this experiment is to evaluate the robustness to noise of our proposed approach against available approaches. For the comparison, we choose the algorithms proposed in [13], [15] which sequentially combines the Fourier transform and parameters estimation method. The reason why we choose this algorithm is that it is suitable for noisy image. See Fig 9 and Fig 10 for two noisy samples of the forged images shown in Fig. 3 (a) and (c). Fig. 9 compares the results from our method against those from the algorithm in [13] with strong noise 20 dB. The radius r_c of centered ring is obtained with $r_c = 8$ from Fig. 9 (b), as defined in

Section III-A. Here, the defocus blur radius $R = 4.5$ for the noisy image in Fig. 9 (a). However, the defocus blur radius $R = 6.24$ for the noisy image is estimated by the algorithm in [13], where the radius of the first centered ring in the spectrum shown in Fig.9 (c). Simultaneously, Fig. 10 compares the results from our method against the algorithm in [15] with strong noise 20 dB. As can be seen, the motion direction $\theta = 45^\circ$ for the noisy image is estimated by the Radon transform, as shown in Fig. 10 (b). From Fig. 10 (c), the second parameter of the motion length d is detected with $d = 9$. However, the motion length $d = 11.6$ for the noisy image is estimated by the algorithm in [15]. From Fig 9 and Fig 10, the comparison shows that our algorithm is more accurate to parameters estimation of noisy image than available algorithms.

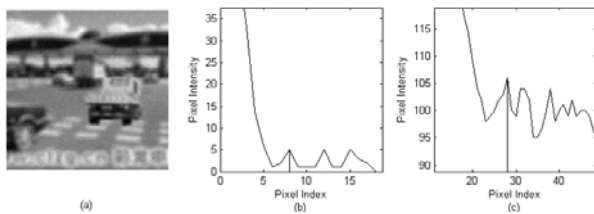


Figure 9. Comparison with [13]. (a) is the noisy version of the forged image shown in Fig. 3 (a) with SNR 20. (b) is estimated the radius of the centered ring in the cepstrum by our algorithm. (c) is estimated the radius of the centered ring in the spectrum by the algorithm in [13].

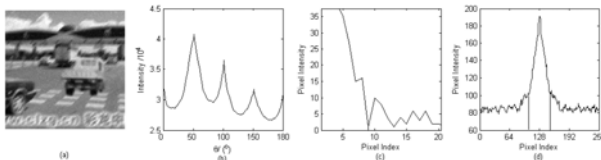


Figure 10. Comparison with [15]. (a) is the noisy version of the forged image shown in Fig. 3 (c) with SNR 20. (b) is estimated the motion direction by Radon transform. (c) is estimated the motion length by our algorithm. (d) is estimated the distance between two parallel dark lines near zero by the algorithm in [15].

Furthermore, We also randomly selected 100 natural images from the internet, and each of them was blurred by applying a blurring kernel with $R = 5$ or $d = 10$ and $\theta = 45^\circ$, respectively. We spliced different objects into the blurred backgrounds of the images and applied most common Gaussian blur, obtaining 100 spliced defocus-blurred images and 100 spliced motion-blurred images. Subsequently these spliced images were contaminated by zero mean white Gaussian noise with different noise levels. Fig. 11 and Fig. 12 compare the performance of our algorithm (denoted by R+C method) against available algorithms in [13], [15] (denoted by R+S method) with different noise levels. The comparison shows that our algorithm is more robust to noise than the available algorithm. In particular, It is clear that our algorithm outperforms the available algorithm by a large margin at low signal-to-noise ratio (SNR).

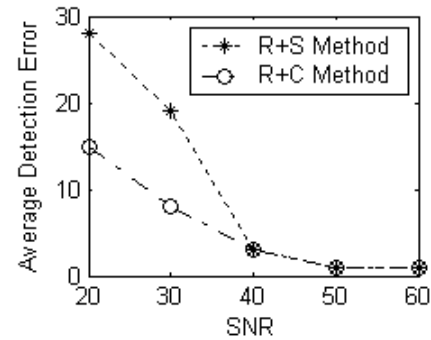


Figure 11. Comparison of the average detection errors. 'R+S' denotes the method in [13]. 'R+C' denotes our method.

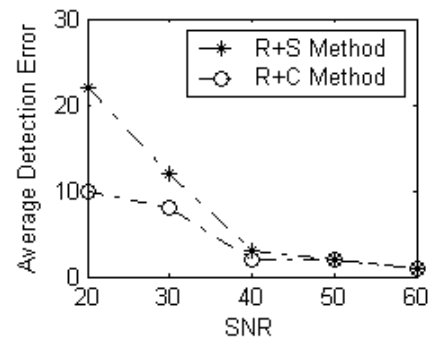


Figure 12. Comparison of the average detection errors. 'R+S' denotes the method in [15]. 'R+C' denotes our method.

V. CONCLUSION

We have presented a technique for detecting spliced blurred images through blind image restoration. Our technique first estimates the blur parameters from the cepstrum of suspected image, then restores the given image based on constructed blurring kernel. If the suspected image undergone artificial blur, in general, is unlikely to be completely consistent with the blur parameters in the rest of the image. So, the regions of the restored image which show inconsistent ringing effect are then detected and displayed to the user. We have also developed a REM to provide robust segmentation. Experimental results show that our technique provides good segmentation of regions with inconsistent blurs and is suitable for both defocus blur and motion blur. Moreover, we could clearly see that our algorithm is more robust to noise than the available algorithms. However, no method can be perfect and detect all kinds of image forgery. Future works will deal with the drawbacks presented in our proposition when the background regions and the spliced regions have consistent blurring kernels.

VI. ACKNOWLEDGEMENTS

This work was supported by the National Natural Science Foundation of China (Grant No. 61371113, U1204606), the Natural Science Foundation of Jiangsu Province (Grant No.BK20130393), the Natural Science Foundation of the Jiangsu Higher Education Institutions of China (Grant No. 12KJB510026, 12KJB510025) and

the Scientific Research Foundation for the PhD (Nantong University, Grant No.03080416, 03080415).

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