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Edge-based Blur Metric for Tamper Detection

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Abstract. *In order to check the aboriginality and integrity of a digital photograph, a blind forensics scheme for detecting blur manipulation is proposed in this paper. A cost-effective local blur estimator is designed to measure the blurriness of each pixel along a doubted edge. Consistency metric of such a blurriness sequence is constructed based on the deviation from its linear fitting. Then the metric is used as evidence for identifying blur operation. Experimental results both on synthetic and natural images have shown the efficiency of our proposed blur forensics scheme.*
Keywords: Image forensics, Blur detection, Edge-based blur metric

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1. **Introduction.** In the digital world, powerful and low-cost digital technology has made it possible to create sophisticated and compelling photographic forgeries. Hence we can no longer take the authenticity of photos for granted. It is urgent to develop blind forensic techniques to assure the integrity and authenticity of digital images [1]. Localized image manipulation such as manual blur and local contrast enhancement are usually used as post-processing to retouch splicing boundaries, which is a familiar mode for creating sophisticated forgeries. So detecting the existence of manual blur can help us discover image tampering and verify an image's originality. In this work, we focus on the blind detection of blur operation.

In previous work, several image splicing detection algorithms based on bicoherence [2], camera response function [3] and phase congruency [4] have been developed. A common assumption of them is that no post-processing has been done to the spliced image, which is not suitable in practice, especially when a sophisticated forgery is expected to create. In fact, such splicing detection methods are easily invalidated by post blur retouching. A copy-move forgery detection algorithm is proposed in [5] by tracking trails of sharpness/blurriness adjustment. In the paper [6], the authors present a method that could reveal blurred regions which indicate possible tampering. However, they are all easily frustrated by the edge-based type of blur manipulation. Because the employed blurriness metric is estimated in region-level, which is sensitive to both image content and local edge-level blur. A blurred edge detection scheme is proposed using edge preserving smoothing filtering and mathematical morphology in [7]. Although it shows a visual detection result of a manual blur instance, quantitative probability metric for the occurrence of blur operation has not been given.

To conquer the deficiency of such previous work, the problem of identifying blur alteration is explored deeply in this paper. Specifically, we attempt to answer this question: Given a digital photograph, can we determine its blur operation history accurately and blindly? Or more generally, where and which edge has been blurred artificially? To accomplish this blur forensics task, we design a semi-automatic local blur detection algorithm based on step edge signal analysis. Once a suspicious edge is selected as splicing boundary in manner of interactively, a cost-effective blurriness estimate procedure is performed along the edge orderly. Then consistency checking is implemented on the computed blurriness sequence. Statistical difference between blurriness curve and its linear fitting version is to be characterized and utilized as metric for the trail of artificial blur. Edges which lack consistency and produce larger metric value are proved to be manipulated by blur tampering.

The rest of this paper is organized as follows. In Section 2, we present a low cost but effective blur estimate method based on step edge analysis. Tamper assurance scheme based on coherence evaluation of the edge-based blurriness map is formulated in Section 3. Experiments designed to assess the performance of the blur forensics scheme are shown in Section 4. Finally, we draw our conclusions in Section 5.

2. **Edge-based Blur Estimation.** As the first step of our blur forensics procedure, some suspicious edges should be designated firstly. In fact, only two pixels on an edge are needed to be pointed out and then are regarded as two ends of an edge segment to be analyzed. Such edge segments can be located by many classical edge detectors like Canny and Sober. Subsequently, local blur estimation will be deployed at each pixel of the segments.

The blur estimator is built upon a step edge model and a blur kernel. In the scenarios of image composition, it is very likely to introduce discontinuity or an abrupt change at splicing points [2]. When two regions with intact content are copy-moved together to make a forgery, new boundaries with step shape are incurred naturally. Such new edges without any post-processing can be simulated as step function mathematically [8]. For each pixel on the chosen edge segment, the original composite edge $u(x)$, which has not been retouched, is shown in Figure 1. That is,

$$u(x) = \begin{cases} A + H, x \geq 0 \\ A \quad\;\;\, , x < 0 \end{cases}, \quad x \in \mathbf{Z} \tag{1}$$

where x is the position, A and H denote an edge's one-side amplitude and height respectively. $\mathbf{Z}$ signifies the integer set.

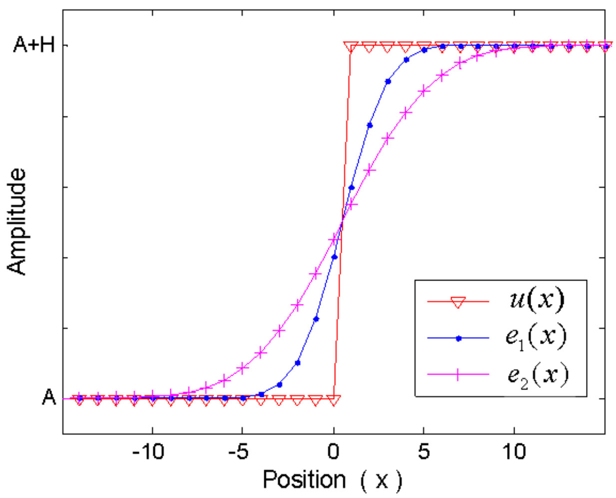


FIGURE 1. Model for composite boundary $u(x)$ and its two blurred versions.

In reference to retouching, the composite edge is often blurred by manual blur manipulation in an image editing environment such as Photoshop, CorelDRAW and Maya. In fact, such specific blur operations are desired to simulate natural imaging blur, which makes the composite look more realistic. Without loss of generality, the referred blur kernel can be modeled by a normalized Gaussian function:

$$g(x,\sigma) = \frac{1}{\sqrt{2\pi}\sigma}\exp(-\frac{x^2}{2\sigma^2}), \quad x \in \mathbf{Z} \tag{2}$$

where σ is the unknown blur radius to be estimated. Then a blurred composite edge can be generated by the convolution between the original composite edge and a Gaussian blur kernel, which is denoted as follows:

$$\begin{aligned} e(x) &= u(x) \otimes g(x,\sigma) \\ &= \begin{cases} \frac{H}{2}(1+\sum\limits_{n=-x}^{x} g(n,\sigma)) + \mathrm{A}, x \geq 0 \\ \frac{H}{2}(1-\sum\limits_{n=x+1}^{-x-1} g(n,\sigma)) + \mathrm{A}, x < 0 \end{cases}, \quad x \in \mathbf{Z} \end{aligned} \tag{3}$$

Two blurred edges, $e_1(x)$ and $e_2(x)$, are displayed in Figure 1. They are generated by two blur kernels with different radius. It can be found that such two blurred edges exhibit different slope at the edge center. The larger the kernel radius is, the smaller the absolute value of its slope is. Through capturing this character, a low cost kernel radius estimation strategy based on edge slope is to be explored.

The derivative of a blurred edge $e(x)$ can be obtained:

$$\begin{aligned} |\nabla e(x)| &= |\nabla u(x) \otimes g(x,\sigma)| \\ &= |\mathrm{H}\delta(x) \otimes g(x,\sigma)| \\ &= \frac{|H|}{\sqrt{2\pi}\sigma}\exp(-\frac{x^2}{2\sigma^2}), \quad x \in \mathbf{Z} \end{aligned} \tag{4}$$

where $|\bullet|$ means taking absolute value. We can find that absolute value of the slope signal has a form of Gaussian function, which achieves maximum at the edge center $x = 0$. Hence,

$$\max_x(|\nabla e(x)|) = |\nabla e(0)| = \frac{|H|}{\sqrt{2\pi}\sigma} \tag{5}$$

In the end, an estimator of kernel radius related with blur operation can be obtained:

$$\sigma = \frac{|H|}{\sqrt{2\pi} * (|\nabla e(0)|)} \tag{6}$$

Here, σ represents the blur metric of an edge pixel. We can see that blur estimation from the formula (6) is with low cost, because no complex computation is involved. However, accurately measuring the edge slope, $|\nabla e(0)|$, is not an easy task, which determines the estimate precision of blur radius directly. When both two blur operators have small radius, the central slopes become so large and similar that they can't be differentiated precisely by pixel-level calculation. So a refined slope computation method based on sub-pixel interpolation is afforded. Super-resolution versions of the discrete edges are gained to compute the slope more accurately. It is necessary to point out that our blur estimation method performs well only on edges with step shape, which appear in almost every natural image. In such scenarios, edge height $|H|$ refers to the difference of two average amplitudes calculated on each side. Transition range with a certain distance should be left for computing slope extremum. The proposed local blur measure algorithm is also applicable for natural step edges [8]. Because defocus blur of such natural edges is the same as the manual blurring performed on splicing boundaries.

The blur estimate algorithm can be summarized as follows:

- Obtain the image's edge map by Canny detector.
- Construct and interpolate one-dimensional sequence $e(x)$ at each step-edge pixel.
- Calculate edge height $|H|$ and the max. slope $\max_x(|\nabla e(x)|)$.
- Estimate blur radius σ using the formula (6).

3. **Tamper Detection Method.** With respect to image blur, there exist two kinds of blur in digital image forensics circumstance. One is natural blur including defocus and motion blur, which is generated during optical imaging process. The other is artificial blur incurred by deliberate manipulation. To discover the trail of artificial blur operation is the main objective of tamper detection.

Manual blur operation is often employed to retouch boundaries after image splicing occurs. In practice, it is usually implemented by handwork in a digital image editing environment such as Photoshop, where Gaussian blur filters with different radius and rigidity are frequently adopted. However, blur manipulation with different intensity may emerge at different positions of one boundary. That attributes to various length and complexity of boundaries. We can't ensure that the artificial unsharpening operation is always performed evenly enough. As a result, we believe that a step edge segment, which has been blurred by handwork, is provided with incontinuous blur radius sequence. Such a sequence will deviate from linearity to some extent. On the contrary, the same metric of a natural edge exhibits good linear coherence, which is determined by the inherence of imaging geometry.

The proposed tamper identification method is based on assessing consistency of the estimated blur radius along an edge segment, which is doubted as a splicing boundary and pointed out interactively. To begin with, a one-dimensional blur vector is created for each edge segment by the proposed blur estimation method in section 2. Each element of it records the estimated blur radius at the corresponding edge pixel in sequence. That is,

$$\sigma = [\sigma_1, \sigma_2, ..., \sigma_i, ..., \sigma_N] \tag{7}$$

where N corresponds to the total number of pixels contained in the edge segment.

In fact, some elements of σ can't be gained occasionally due to the complexity of edge regions. Expected step edges may not appear at each pixel position. Then the elements without metric are filled with local average of neighboring estimations. So far a complete blur vector has been built. Consistency metric of such a blur vector is designed as:

$$c = Var[\sigma - linear\_fitting(\sigma)] \tag{8}$$

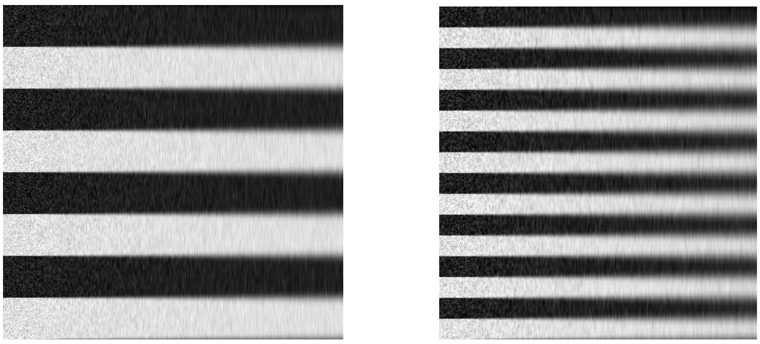
where $linear\_fitting(\bullet)$ is a linear fitting function, which converts σ into its corresponding linear fitting sequence.

Threshold-based discriminant strategy is used to identify manual blurred edges. Edge segments with lower score c are to be considered as unnatural or abnormal. It can be claimed that some post manipulations such as blur tampering have been performed on these edge regions. To prevent being deceived by inverse direction linear blur tampering, common sense for judging defocus direction is introduced. Linear blur along the direction against edge focusing is still judged as blur modification.

4. **Experimental Results and Discussion.** In this section, we test the proposed blur estimation method on some synthetic images. Tamper detection results on natural images and discussion of them are presented in another subsection.

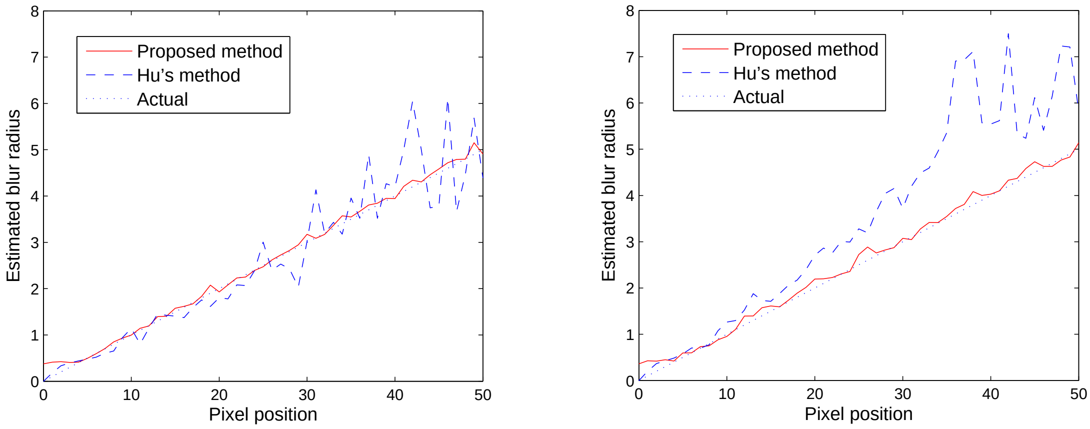
4.1. **Assessing the blur estimation method.** To prove the efficiency of the proposed blur measure method, we compare it with Hu's blur estimation method [8]. The similar experimental setting is prepared. Synthetic images with multiple step edges blurred by a one-dimension Gaussian blur kernel are used, as shown in Figure 2. The blur radius increases linearly along the edge from 0.1 to 5. Gaussian noise with normalized variance 0.01 is added to simulate imaging and channel noise. Distance between adjacent step edges D has been set as 50 and 20, respectively. Optimal blur estimation results for both methods are shown in Figure 3.

We can see that our proposed method performs well on the whole range of blur radius. The actual radius has been estimated without any large deviation. By contraries, Hu's metric has obvious fluctuation, especially on the range of large radius. The smaller the distance between neighboring edges is, the more difficult the blur estimate becomes due to the intense disturbance of neighboring edges. For D=20, we can see from Figure 3(b) that Hu's method degrades seriously while our proposed method still behaves perfectly. As for Hu's method, much larger error occurs especially in the case of intense blur.



(a) (b)

FIGURE 2. Synthetic blurred images. (a) D=50. (b) D=20.



(a) (b)

FIGURE 3. Estimated blur radius on the synthetic images. (a) D=50. (b) D=20.

4.2. **Blur detection results and discussion.** We test our proposed blur forensics algorithm on several typical and sophisticated forgeries. To find and locate the trail of blur manipulation in these images, several suspicious edge segments are chosen firstly. Estimated blur radius is displayed as a curve along the position of edge pixels. Then such curves' linear consistency can be observed and measured, which helps users discovering which edges have been retouched.

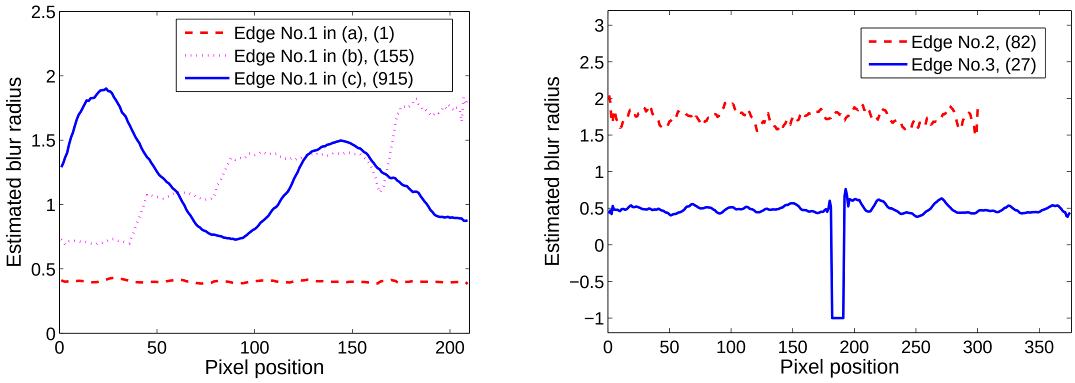
A spliced image (named as 'Door') from *Columbia Uncompressed Image Splicing Detection Dataset* [3] is used as a test image, as shown in Figure 4 (a). The splicing boundary is displayed by red line and no post-processing has been executed on it. Two times of different manual blur are operated randomly on this boundary, as shown in Figure 4 (b) and Figure 4 (c), respectively. Here, such two time blur manipulations are performed by Gaussian blur tool with randomly selected parameters in Photoshop CS4. Comparative blur effects are gained on the splicing boundary, both being perceived as authentic. Together with other two natural edges, which are marked by magenta and blue line respectively, three edge segments are to be checked by our blur forensics procedure.

(a) (b) (c)

FIGURE 4. Test image 'Door'. (a) Unaltered spliced image, three edges are to be analyzed: *Edge No.1* (red line) is the splicing boundary, *Edge No.2* (magenta line) and *Edge No.3* (blue line) are natural edges. (b) One blurred version of the splicing boundary. (c) Another blurred version.

Estimated blur radius vectors are plotted as curves and shown in Figure 5. We can see that curves of blurred boundaries have much larger dithering than both two natural edges and the original splicing boundary. Consistency metric of the curves, which describes the deviation from corresponding fitting lines, is also measured and given in parentheses. One can find that splicing boundaries blurred artificially hold greater score (155 and 915) than that of natural edges (82 and 27). From these data, we can easily identify which edge has been blurred manually through a simple thresholding classification. For the natural edge segment of a white paper on the door, named *Edge No.3*, a range without efficient estimation (denoted by -1) appears on its metric curve. It is caused by a corner with acute angle on this edge segment. Around the corner step edge slices can't be gained.

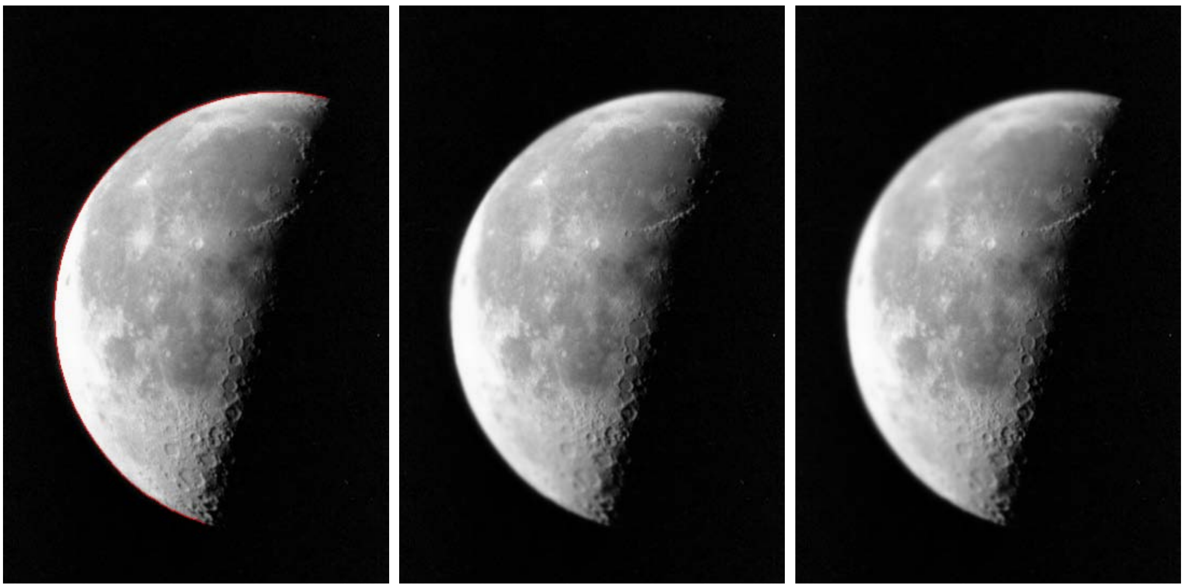
To further assessing the performance of our proposed blur forensics algorithm, we test another grayscale image 'Moon' and its two altered copies, in which local blur operations are randomly on the arc boundaries of moon. They are shown in Figure 6. Here, blur with different intensity are performed. The one with larger blur radius is shown in Figure 6 (c), which is more blurry than the other altered copy. However, we can't indicate whether anyone of them has been blurred or not blindly. The edge segment to be evaluated is marked by a red line. Detection results are shown in Figure 7. We can see that metric curves for blurred edges fluctuate more seriously than the original



(a) (b)

FIGURE 5. Estimated blur radius on 'Door'. Consistency metric for each curve is scaled by 10^4 and given in parentheses. (a) for *Edge No.1*. (b) for *Edge No.2* and *Edge No.3*.

untouched one. Correspondingly, the metric for capturing linear consistency differs obviously, 584/694 compared with 90. These scores imply the separability of blur operation and non-alteration, under the identical differentiation criterion of image 'Door'. In fact, nonlinearity of the estimated blur curve with unblurred edge still exists to some extent, which can be seen from the random vibration along the curve. That will increase the risk of false alarm for our forensics scheme. Loss of desirable step property on analyzed edges maybe the cause for such deficiency.



(a) (b) (c)

FIGURE 6. Test image 'Moon'. (a) Unaltered original image, one edge to be analyzed is denoted by red line. (b) One blurred version of the edge. (c) Another blurred version.

We must admit that there exists the possibility to deceive our proposed forensics algorithm. For example, malicious edge retouching with elaboration and weak region-level blur

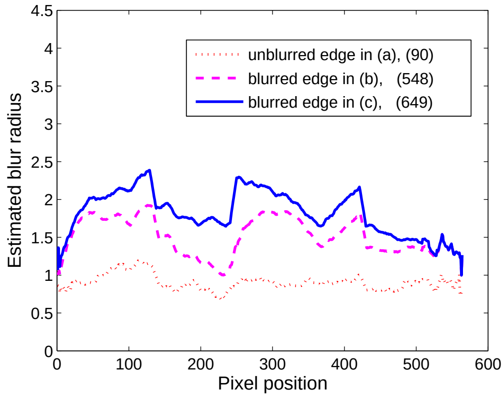


FIGURE 7. Estimated blur radius on 'Moon'. Consistency metric for each curve is scaled by 10^4 and given in parentheses.

are still hard to be discovered. Such kinds of blur manipulation, other than edge-based retouching, can be explored in the further work.

5. **Conclusions.** We propose a novel blur operation detection approach via edge-based blur estimation, consistency checking and measure. The method is fully blind and passive, no extrinsic message embedding is needed. The creative edge-based blur estimator is proved effective both on theory and practical test. The linear consistency is assessed based on linear fitting and statistical metric. Experimental results show promising performance in detecting and locating trails of blur manipulation.

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