# Image Splicing Detection using Gaussian or Defocus Blur

Anurag Das, Abhishek Medhi, Ram Kumar Karsh, Rabul Hussain Laskar

***Abstract* - Tampering images to create false ones using photo manipulation software is very easy. Tampering may be in the form of image splicing. Image Splicing involves the introduction of a selected region from one image into another with the aim to alter its content. Splicing may be in the form of blurred regions introduced via Gaussian blur. In this paper, a method based on inconsistencies in Gaussian blur is used to test the authenticity of an image. Gaussian blur of an image is first evaluated and standard deviation obtained is used to de blur the image. Forged region with different value of standard deviation are bound to show ringing effects, which highlight the forgery.**

***Index Terms – Image splicing, Gaussian blur, standard deviation, image authentication.***

## I. INTRODUCTION

Digital Image Forensics deals with verifying the authenticity of an image. The use of excessive photo manipulation software has made this difficult to certify. The same software used for minor changes can also bring about drastic alterations, often at times creating an entirely different image.

Digital Image may be manipulated in a way such that it becomes very difficult to detect it perceptually. Sophisticated software have only made this task easier. Forgeries in various fields like journalism, scientific publications, medical imaging are particularly alarming as they can distort the truth to an extent that a person's identity is put at risk.

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To expose such forgeries, techniques preferred fall into two categories: active forgery detection and passive forgery detection. In case of active forgery detection, additional information in the form of digital watermarks or signature or some parameter of the original image may be present. However, this is usually not the case, as most cameras cannot embed information in the image. Passive techniques, on the other hand do require not any additional information and forgeries if any are highlighted using the available content of the image. [1][2]

Digital images may be tampered in several ways. Here, we focus on a form of tampering called Image Splicing. Image Splicing involves creating forged images by compositing regions from one or more different images. Thus splicing can be used to hide important details or introduce new objects into the image, drastically changing the image. Many techniques to detect such forgeries have been proposed in recent times. Some of these include: Using geometric invariants and camera characteristics consistency where inconsistency between the light direction and shadows is highlighted [3], Using the JPEG compression quality to test for differences in the quality of compression of different regions of the image [4], Using differences in the Sensor Noise pattern to highlight inconsistencies [5][6]. However, in such approaches, it is assumed that the image has not undergone any post-processing. To tackle such cases forgery detection using different types of blur is used.

Presence of background blur often poses a restriction on the observer, as objects do not appear sharp. Fortunately, the person making the forgery is also faced with the same problem and thus introduces a spliced object into the image with an approximate value of blur similar to the background. This fact can be made use of to check whether an image is tampered with. Using discrepancies in motion blur in various regions of an image by Kakar[7], spliced regions have been exposed. By using the blur degrees and blur information of various regions of an image, splicing regions were detected by Bahrami,Kot,Jiayuan[8]. Using the defocus blur information of the blur edges and natural images, to create a difference of defocus blur parameter, which exposed spliced regions as highlighted by Song and Lin [9].

In this approach a splicing detection based on Gaussian blur is proposed to detect Splicing. In this approach, it is assumed that the image has a natural blur in the form of Gaussian blur and Scale Space theory as highlighted by Lowe [10] is used to calculate the standard deviation of the overall image, using which the image is de blurred. The resultant image will have pronounced ringing effects at the spliced regions as they are created with a different value of blur. Ringing effect of these regions are calculated and values obtained are used to test the authenticity of the image. The rest of the paper is organized as follows: II. Scale Space Theory III,. Blur Models, IV. A property of the Gaussian Kernel, V. Proposed Method, VI. Results

## II. SCALE SPACE THEORY

The Scale Space Theory is used for handling image structures at various scales. Here, a family of smoothed images given by a parameter represents an image. The importance of scale space theory is highlighted by the fact that it can be used to show how an object behaves at different scales.

A building may appear as a single object from about 500 meters away but up close, the windows, the balconies come into view. This an object behaves differently depending on the scale at which we view them. Such a problem may be solved if we have access to all scales, if prior information is not available. In other words, we need a multi scale representation of the available image.

To achieve such a multi scale representation, scale space theory takes the help of different blurring kernels to obtain different scales. However, it must be ensured that the structures at coarse scales are related to corresponding structures at fine scales. New structures must not result because of smoothing. Thus, the scale space must be linear and only Gaussian kernel can be shown to create such a linear scale space. The axioms that support the uniqueness of the Gaussian scale space include linearity, shift invariance.

Thus to create the scale space, an image is blurred by a series of Gaussian kernels with increasing values of variances. At large variances, fine scale information is averaged out and only large-scale information is left. The obtained scale space is then used to create a Difference of Gaussian (DoG) format.

## III. BLUR MODELS

Different blurs introduced in an image are identified by means of their blurring kernel. Thus to identify the blur in an image we need to identify its kernel. Some common types of blurs for camera systems include motion blur, defocus blur. The defocus blur is because of the optical system's inability to focus and motion blur arises because of the relative motion between the object and the camera. The blurring phenomenon maybe modelled as a convolution of an image with a blurring kernel or point spread function (PSF) along with some additive white Gaussian noise.

$$I(i,j) = (F * H)(i,j) + N(i,j) \tag{1}$$

Where I refers to the resultant blurred image, F refers to the sharp image, H is the blurring kernel and N is the noise and i,j refer to the pixel coordinates.

### *A. Motion Blur*

For the case of horizontal uniform motion blur, the blur kernel maybe modelled as a one-dimensional vector of length L.

$$Pu\ (i; j) = 1/L\ [1; 1; :::; 1]_{1*L} \tag{2}$$

### *B. Defocus Blur*

For the case of defocus blur, the blurring kernel maybe modelled as a circular symmetric cylinder function as

$$Pu\ (i; j) = 1/\frac{1}{\pi R^2}\sqrt{i^2+j^2} \le R\ , \tag{3}$$

Where R is the blurring radius.

Wu [11] used this model to identify the blur in cepstrum domain. However to represent natural or defocus blur, a Gaussian filter is made use of.

A two dimensional Gaussian blur filter maybe represented as

$$Pu\ (i; j) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{i^2+j^2}{2\sigma^2}} \tag{4}$$

Where σ is the standard deviation of the Gaussian kernel.

Parameter estimation for such kernels takes advantage of the uniformities present in the frequency domain. Because of the periodic zero pattern, dark lines are observed in the corresponding spectrum of the blurred images, which may be used to calculate the blur parameter. In the case of defocus blur images, a continuous pattern of disks maybe observed in the spectrum of the blurred image which may then be used to calculate the blurring radius [11]. For the case of Gaussian blur, periodic zero pattern based on frequency domain knowledge cannot be used because periodic zeroes do not exist. Although Gaussian blur is considered to be a kind of defocus blur, it cannot be operated upon as such because of the different nature of its kernel, rather an approach based on Scale Space as proposed by Robinson,Roodt[12] is used.

## IV. A PROPERTY OF THE GAUSSIAN KERNEL

The Gaussian kernel used to produce the Scale Space representation has zero mean. Mathematically, it can be represented as

$$G(x,\sigma^2) = Ae^{-\frac{x^2}{2\sigma^2}}, \tag{5}$$

Where A is the amplitude, $\sigma^2$ is the variance, its square root is the standard deviation. When two Gaussians are convolved, they may be represented as

$$G(x,\sigma^2_A)* G(x,\sigma^2_B) = G(x,\sigma^2_A + \sigma^2_B) \tag{6}$$

When a Gaussian with standard deviation $\sigma_A$ is convolved with another Gaussian with standard deviation $\sigma_B$, the resulting variance may be represented as $(\sigma^2_A + \sigma^2_B)^{1/2}$. If the difference between the obtained Gaussian and original Gaussian with standard deviation $\sigma_B$ is taken, then we obtain the error between the two Gaussians.

$$E = G(x,\sigma^2_A) - G(x,\sigma^2_A + \sigma^2_B) \tag{7}$$

If this error is plotted for different values of $\sigma_B$, keeping $\sigma_A$ as constant, the obtained curve is found to contain a point of inflection. This point of inflection can be determined by checking the extrema in the first derivative of the error curve. This point of inflection is found to correspond to the actual value of standard deviation.

## V. PROPOSED METHOD

A method based on blind image restoration is proposed. In this method, standard deviation of the Gaussian blur is estimated. Using the obtained value of Gaussian blur, the image is deblurred using Richardson-Lucy algorithm. In the deblurred image, spliced regions will show high value of ringing effect and to highlight such areas a measure of ringing effect is obtained as proposed by Wang, Zeng and Yuan.

### *A. BLUR ESTIMATION*

To estimate the standard deviation of the blur used in the original image, the image is blurred a range of Gaussian kernels with increasing values of standard deviation. This is the same approach as used by Lowe. Here, the image is first blurred with a standard deviation of one. This value is subsequently doubled 5 times. This doubling of the standard deviation is represented as an octave. Again, each octave is divided into 10 parts and the blurred images for each value of standard deviation is obtained. Thus, the original blurred image, after blurring again may be represented as

$$D(\sigma_2) = F*G(x,\sigma^2_1)*G(x, \sigma^2_2)$$
$$D(\sigma_2) = F*G(x,\sigma^2_1+ \sigma^2_2) \tag{8}$$

Where D represents the Scale Space for different values of $\sigma_2$ and $F*G(x,\sigma^2_1)$ represents the original image, where F is the sharp image.
The error between the input image and different images in the Scale Space is then given by,

$$E(\sigma_2) = |F*G(x,\sigma^2_1) - F*G(x,\sigma^2_1+ \sigma^2_2)|$$
$$E(\sigma_2) = F*|G(x,\sigma^2_1) - G(x,\sigma^2_1+ \sigma^2_2)| \tag{9}$$

The absolute error response between the original image and obtained images from the Scale Space is similar to that of equation no. (7), thus the same approach can be used to find the standard deviation of the original blurred image. To find the point of inflection, $dE/d\sigma_2$ is calculated using

$$dE = E*[-1,1] \tag{10}$$
$$d\sigma_2 = \sigma_2*[-1,1] \tag{11}$$

The curve of $dE/d\sigma_2$ will possess a distinct maxima and the $\sigma$ value corresponding to this maxima will represent the point of inflection. This corresponds to the standard deviation of the original image.

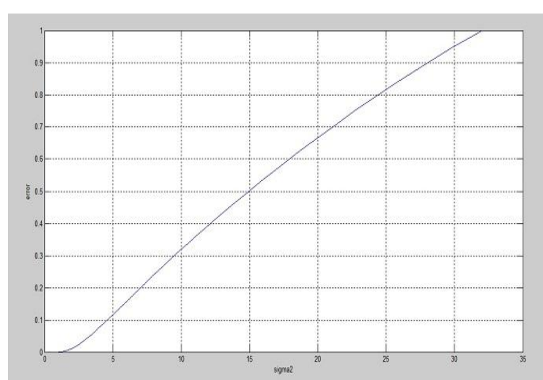


Fig. 1. Error response between the cameraman image blurred with standard deviation $\sigma_1 = 5$ and varying values of $\sigma_2$.

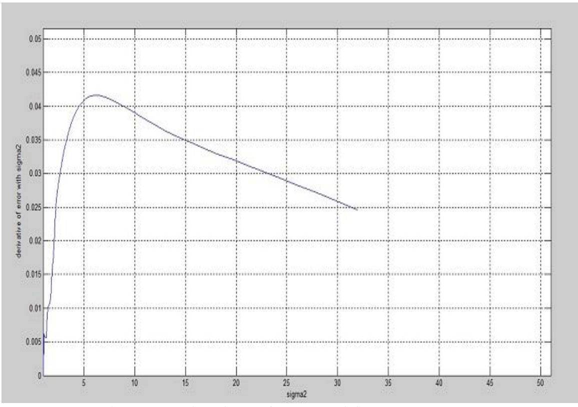


Fig. 2. Derivative of Error with respect to $\sigma_2$.

### B. BLIND IMAGE RESTORATION

With the help of the obtained value of standard deviation, the blurring kernel is estimated. The input image is then restored using Richardson Lucy algorithm.

Here, classical R-L Blind Restoration is used to restore the blurred image and number of iterations used is 20. The standard deviation obtained was because of contribution from the entire image; however, spliced regions are blurred with different values of standard deviation. Hence, these will have some ringing effect. Thus if the ringing effect is measured is found to be above a certain threshold, a region maybe declared spliced.

### C. RINGING EFFECT MEASURE

Spliced regions with different values of standard deviation will show high value of ringing effect. To quantify this ringing effect, the measure proposed by Wang, Zeng and Yuan [13] is used which calculates the sum of absolute pixel gradients. The restored image is divided into several blocks and ringing measure for each block is calculated. The restored image $I_r(i,j)$ may be represented in several blocks as

$$c_{x,y}(i,j) = I_r(i,j)(1+k(x-1):kx,1+(k-1)y:ky),$$

where $c_{x,y}(i,j)$ denotes the sub-block with a=y= 1,2,…,floor(M/k).

Ringing measure along rows is given as

$$REM_{row} = 1/k \mid c_{x,y}(i,j+1) - c_{x,y}(i,j) \mid \qquad (12)$$

Ringing measure along columns is given as

$$REM_{column} = 1/k \mid c_{x,y}(i+1,j) - c_{x,y}(i,j) \mid \qquad (13)$$

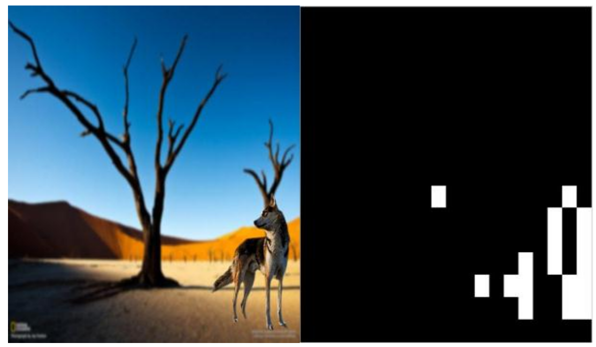
Ringing measure of each sub-block is then represented as $REM(c_{x,y}) = \max(REM_{row},REM_{column})$.

The sub-block is said to be spliced if this value is found to be above a certain threshold. Here, the threshold is selected as 1100.

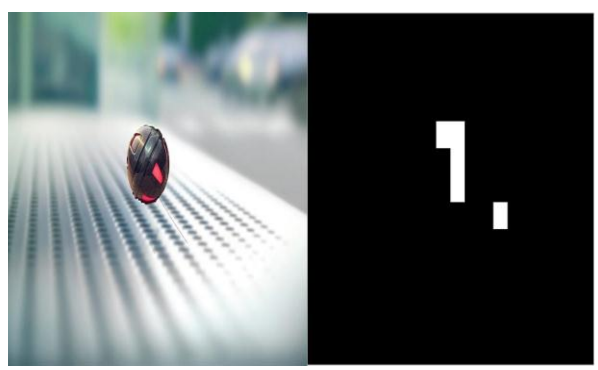
## VI. RESULTS

Experiments were performed on several test images. A database of 50 images was created. Original images were taken and different objects were spliced into them by applying Gaussian blur. Adobe Photoshop CC was used for this purpose.

To test the validity of this method, it is compared with the method highlighted in [11].


IMG 1.


IMG 2.


IMG 3

Here only continuous blocks have been considered to be forged, isolated blocks in the results are not considered to be a part of the forged region.

The obtained value of standard deviation tested with cameraman image in each case is tabulated below:

| Actual Standard Deviation | Obtained Value Using Proposed Method | Radius of Blur in [11] |
|---|---|---|
| 5 | 5 | 4 |
| 6 | 6 | 5 |
| 8 | 9 | 10 |
| 15 | 17 | 17 |
| 18 | 18 | 19 |
| 20 | 19 | 21 |
| 25 | 23 | 26 |

Image regions with splicing in them have more or less been accurately detected. The method may also be used to detect forged regions, which are blurred heavily in comparison to the rest of the image, although it is rare. To improve upon the results a median filtering pre-processing step is used before blur detection to reduce the effect of noise. It is to be noted however, that the proposed method works well if the forgeries involved are only Gaussian blurred.

## VII. CONCLUSION

The proposed technique is useful in detecting splicing involving Gaussian blur, the standard deviation of which is rather tedious to estimate. The proposed method first finds the standard deviation of the blurred image using scale space representation. The standard deviation corresponding to the inflection point in the error between the blurred image and those because of re-blurring it with different Gaussian kernels. The blurred image is then sharpened with the help of the obtained standard deviation. Ringing is rather prominent in the regions corresponding to the spliced object and based on a suitable threshold, the regions are segmented. The algorithm however works well with only Gaussian blur based forgeries; presence of other kind of blurs may lead to false detection.

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