DETECTION OF BLURRED REGION IN IMAGES FOR FORENSIC APPLICATIONS

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Abstract:

Due to the arrival of new technologies and devices, the crime rate is increasing in developing and developed countries. One such crime is image forgery which can be detected by forensic applications. We propose an idea to identify forgery attack done by blur artifact. In this method, the Region of Interest (RoI) is identified using Histogram Thresholding that involves computation of statistical and color texture analysis. For each RoI, the degree of blur is estimated for distinguishing forged blur artifact from normal blur artifact. The technique is tested by MICC-F220 dataset using MATLAB R2011a. To validate the identified forged blur artifact, we use Fourier and Gabor texture features. [0]

Keywords: Copy–move detection, Blurred forged region detection, Statistical features, Phase congruency, Structural features, feature similarity index

I.INTRODUCTION

With the rapid development of digital image technology, digital images have been integrated into all aspects of daily life. As a result, high-resolution digital cameras and modern image-editing tools such as Photoshop have made the image tampering more easily. Image manipulation methods are classified into image tampering or image steganography.

Forensic means discoveryof evidence to solve a crime, and e-forensics refers to the process of finding electronic evidence in a way thatis legally suitable to solve a crime[2].

One example is illustrated in Fig. 1 where (a) is the original image, (b) is the forged one where the one soldier is removed from the image and (c) is the doubtful regions recognized by the method which works based on identifying blur moments. It is noticed from Fig. 1 (b) that since the person is removed by the devices, it introduces some sort of distortions, such as blur, noise, degradations, etc. Based on this evidence, the method. In the same way, one can expect forged image may contain duplicate objects brought from the same image which is called copy-move forgery. This shows that identifying forgery is hard, and hence, it has become a major topic for the researchers in recent days.[3]

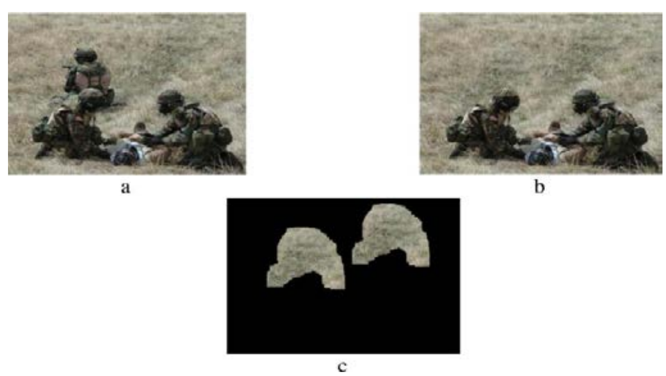

Fig. 1. (a) The original image (b) The forged image (c) The detection result of method

Copy–move forgery is becoming one of the most popular image tampering. Copy–

move forgery is copying a region of an image and pasting it in another location of the same image. The key characteristic of the duplicated regions is that they have the same noise components, textures, color patterns, homogeneity conditions and internal structures. The forgers perform duplicate regions with different geometric and post-processing operations to hide traces and make consistency with surrounding area.

II. PROPOSED METHOD

The recent forgery attack is making forged or duplicate regions blur to create confusion with other blurred regions and non-blurred regions. For such input forged image, first, we propose to segment the Region of Interest(RoI) in the image which includes forged blurred region also because it is a forged region by a copy-move process. As a result, we can expect high contrast values at edges and near edges. Besides, we can also expect uniform texture throughout the object. With these notions, we propose statistical analysis and color texture to segment the Region of Interest (ROI). Since forged blurred region is also an object, it is classified as region of interest. Next, we propose blur metric to estimate degree of blurred regions from the region of interest. This results in blurred and non-blurred region of interest. Due to camera motion or object motion, there are chances of introducing blur in the images which may results in actual blurred regions. To separate forged blurred region from actual blurred region, we propose a new idea of combining Fourier coefficients and gradient based features because it is fact that Fourier high frequency coefficients and gradients are not much sensitive to blur as intensity values and edges. The features are matched with predefined samples to identify forged blurred region. The flowdiagram of the proposed method can be seen in Fig. 2.

2.1. Segmenting region of interest (ROI)

Based on the similarity of the internal structure of duplicated regions, the input image is segmented into homogenous regions. Segmentation of the image is carried out using Histogram Thresholding to capture the main objects in the image using effective statistical image analysis [7]

Histogram is constructed by splitting the range of the data into equal sized bins (called classes). Then for each bin, the numbers of points from the data set that fall into each bin are counted. Threshold value is calculated every time. Based on the Threshold value homogeneous regions are divided into one region. Global Thresholding is used for segmenting the image.

1) Select an initial estimate for T
2) Segment the image using T. This will produce two groups of pixels. G1 consisting of all pixels with gray level values >T and G2 consisting of pixels with values <=T.
3) Compute the average gray level values mean1 and mean2 for the pixels in regions G1 and G2.
4) Compute a new threshold value

$$T = \frac{mean1 + mean2}{2}$$

5) Repeat steps 2 through 4 until difference in T in successive iterations is smaller than a predefined parameterT_0.

3.2. Blurred region detection

To differentiate between normal and blurred regions within a single image, we calculate the blur degree for each region based on the perceptual blur metric model [8]. The algorithmic steps of the blurred region detection are as follows.

Step 1: Horizontal and vertical low pass filtersH_{hor} andH_{ver} are applied to each region *I reg*with size *m*×*n*. Blurred regions *B* are obtained as follows:

$$B_{ver} = I_{reg} * H_{ver}\ ;\ \ B_{hor} = I_{reg} * H_{hor}$$

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Where |*| denotes the convolution operator.

Step 2: The horizontal and vertical absolute differences between the original region and its blurred vision are computed. These image differences are expressed as follows:

$$D_{I_{ver}}(i,j) = \sum_{i=1}^{m-1}\sum_{j=0}^{n-1} |I_{reg}(i,j) - I_{reg}(i-1,j)|$$

$$D_{I_{hor}}(i,j) = \sum_{i=0}^{m-1}\sum_{j=1}^{n-1} |I_{reg}(i,j) - I_{reg}(i,j-1)|$$

$$D_{B_{ver}}(i,j) = \sum_{i=1}^{m-1}\sum_{j=0}^{n-1} |B_{reg}(i,j) - B_{reg}(i-1,j)|$$

$$D_{B_{hor}}(i,j) = \sum_{i=0}^{m-1}\sum_{j=1}^{n-1} |B_{hor}(i,j) - B_{hor}(i,j-1)|$$

Step 3: The variation in the horizontal and vertical absolute difference images is evaluated by the Riemann integral as follows:

$$V_{hor} = \max(f(x),0) = \begin{cases} f(x) = D_{I_{hor}} - D_{B_{hor}}, f(x) \geq 0 \\ 0, \quad\quad otherwise \end{cases}$$

Where V_{hor} and V_{ver} are the horizontal and vertical absolute difference images, respectively. They are computed in the same manner.

Step 4: The variations in the sum of the intensities of difference images $D_{I_{ver}}$, $D_{I_{hor}}$, $D_{B_{ver}}$ and $D_{B_{hor}}$ in a defined range [0–1] are normalized to estimate the vertical and horizontal blur measures as follows:

$$Blur_{I_{ver}} = \frac{\sum D_{I_{ver}} - \sum D_{V_{ver}}}{\sum D_{I_{ver}}}$$

$$where\ D_{vver} = \sum D_{V_{ver}}$$

$$Blur_{I_{hor}} = \frac{\sum D_{I_{hor}} - \sum D_{V_{hor}}}{\sum D_{I_{hor}}}$$

$$where\ D_{vhor} = \sum D_{V_{hor}}$$

Step 5: The blur measure is selected as the maximum value among the vertical and horizontal measures.

$$BME = Max(Blur_{I_{ver}}, Blur_{I_{hor}})$$

Where BME is in the range [0–1]; 0 indicates that the image is sharp and 1 suggests that it is blurred. The degree of blur is low for non-blurred images and high for blurred images. As a result, the detected blurred regions have BME values greater than that of non-blurred regions. If the region BME value is greater than the value of BME at the highest peak, then the region is considered as blurred ROIelse it is considered as non-blurred region ROI.

3.3. Forged blurred region identification

There exists blur in images due to object and camera movements, defocus. In this case, the step proposed in previous section may misclassify actual blurred region as forged region when BME values of the regions satisfy the threshold values. Therefore, we propose a new method for identifying actual forged blurred region from the non blurred region. However, in most cases, the normal blurred region may preserve structure of objects since it is affected by natural blur while forged blurred regions may lose shape due to copy and move process along with blurring procedure. For each blurred region, the proposed method obtain high frequency phase congruency (PCy) coefficients. The PCy for 2D images can be defined in terms

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of the Fourier transform of signal, f (x, y) at point (x, y) in the image as follows[10]

$$PC_y(x,y) = \frac{\sum_n \sum_\theta W(x,y) \lfloor A_{n\theta}(x,y)\Delta\psi_{n\theta}(x,y) - T \rfloor}{\sum_n \sum_\theta A_{n\theta}(x,y) + \varepsilon}$$

Fig. 2 Main steps of the proposed method.

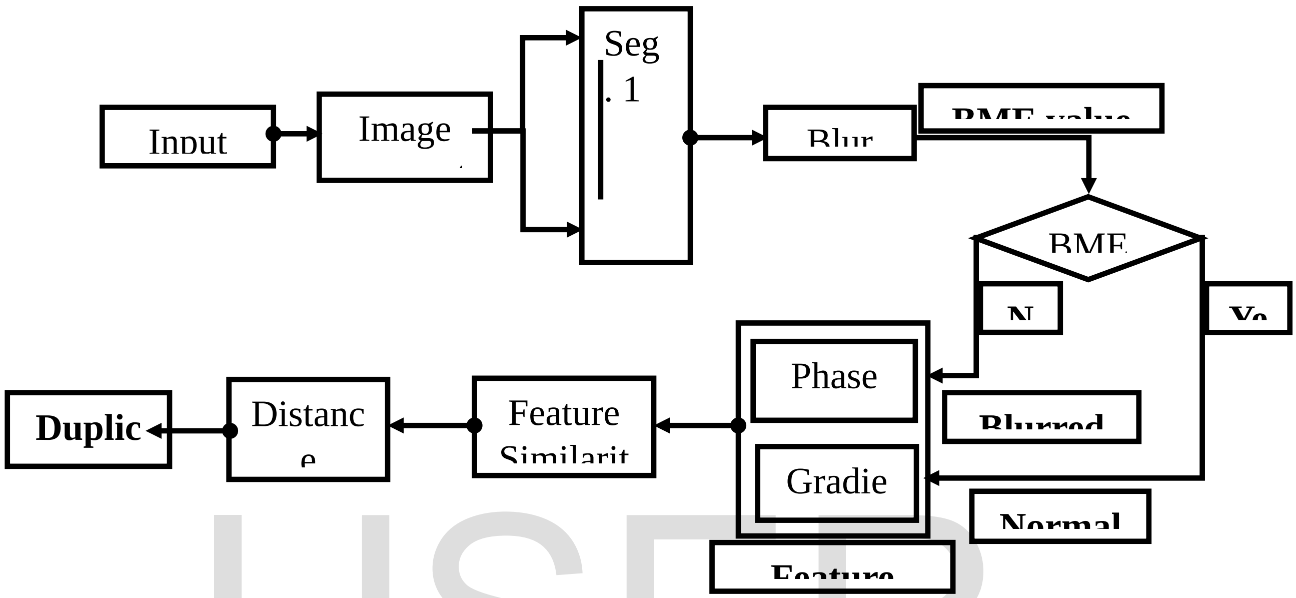


Fig.3. Sample region of interest segmentation of the proposed method

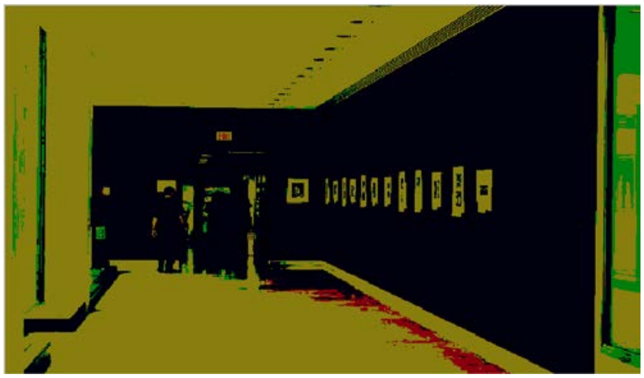
3.a Original Image

3.b Segmented Image

The blur metric value for the image available in the dataset(MICC-F220) are as follows:

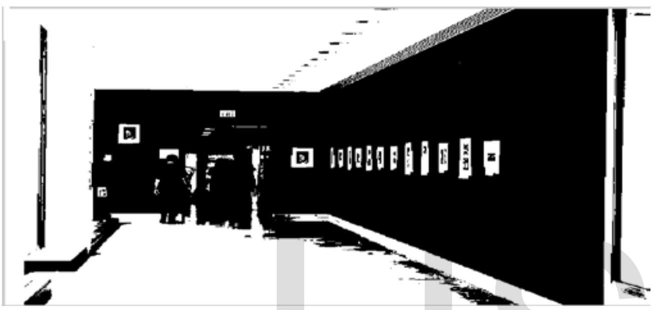
Original image

After Segmentation

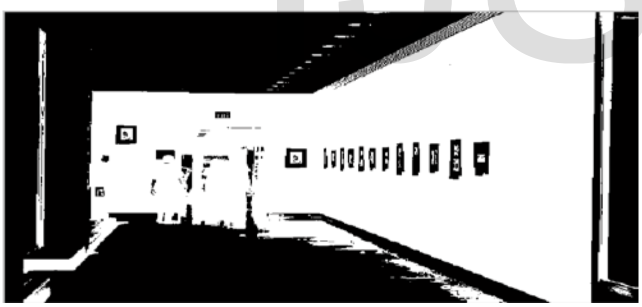


Classification of segments

Segment 1 Blur metric=0.4069



Segment 2 Blur metric=0.4067



where $W(x, y)$ is the weight function of the 2D log-Gabor filter at point $f(x, y)$. $\lfloor\rfloor$ is a floor function that equalizes the enclosed quantity to itself when its value is positive; otherwise, the value is zero. $A_{n\theta}(x,y)$ is the amplitude of the Fourier component at scale n and an orientation angle of filter θ can be defined as

$$A_{n\theta} = \sqrt{e_{n\theta}(x,y)^2 + o_{n\theta}(x,y)^2}$$

Where $e_{n\theta}$(x,y) , $o_{n\theta}$(x,y) are the responses between image $f(x, y)$ and the 2D log-Gabor filter. They are expressed as follows:

$$[e_{n\theta}(x,y), o_{n\theta}(x,y)] = [f(x,y) * M^{e}{}_{n\theta}]$$

Where $*$ is the convolution operator. $M^{e}{}_{n\theta}$ and $M^{o}{}_{n\theta}$ are even and odd symmetric wavelets at scale n = 4 and angle θ= 6, respectively. T is the estimated noise energy. ε= 0.0 0 01 is a small constant that prevents division by zero. $\psi_{n\theta}(x,y)$ is the sensitive measure of phase deviation that is written as follows:

$$\Delta\psi_{n\theta}(x,y) = \cos(\psi_{n\theta}(x,y) - \overline{\psi}_{n\theta}(x,y) \\ - |\sin(\psi_{n\theta}(x,y) - \overline{\psi}_{n\theta}(x,y))|$$

The PCy coefficients are real numbers in the range [0–1]; 0 corresponds to low-frequency components, whereas 1 denotes the highly informative features in the image. For such enhanced blurred ROI**,** the planned method extract three moments, namely, mean (μ), variance (υ), and contrast (c) and it is considered as feature vector, $F = (\mu, \upsilon, c)$. This vector is used for matching to identify forged blurred region. In the same way, the proposed method extracts gradient features for the enhanced blurred ROI as follows: The directional gradients along x and y axis of image I are defined as:

$$\nabla I_x = \frac{L(x+1,y) - I(x-1,y)}{2}$$

$$\nabla I_y = \frac{L(x,y+1) - L(x,y-1)}{2}$$

Where L(x, y) is a derivative of image I with Gaussian kernel. Gradient magnitude is estimated as the square root of the sum of image directional gradients. That is,

$$GM = \sqrt{\nabla {I_x}^2 + \nabla {I_y}^2}$$

GM features are extracted as secondary features from each image region in the forged image and are then combined with PCy features to estimate a similarity index measure of the image region. The three moment's features and gradient features are joined for finding the similarity and dissimilarity to classify whether the given region is forged blurred region or non blurred region using Euclidean distance measure. The regions which have high degree of similarity are classified as forged blurred regions.The Euclidean distance $D(R_x, R_y)$ determines the distance between regions $R_x$and R_y .FX and FY are the corresponding features vectors of N dimensions of the matched regions with edge points. The Euclidean distance is expressed as follows:

$$D(R_x, R_y) = \sqrt{\sum_{i=1}^{N} (FX_i - FY_i)^2}$$

Finally, the duplicate regions are located along with their centroids. The blurred region is highlighted by a circle to visualize the forged region in the image.

IV. EXPERIMENTAL RESULTS

In order to evaluate the proposed method, we consider standard dataset, namely MICC-F220 datawhich contains 110 forged images and 110 original images[8]. These datasets provide small duplicated regions with repetitive patterns which are required to create forgery content using post processing operation such as blurring, additive noise. By using these dataset images, we calculate the blur metric for each region in an image using MATLAB 2011a on Windows 8.1 64-bit Operating Systems with hardware configuration -Intel (R) Core i3 processor@ 1.90 GHz and 6 GB RAM . By using the calculated blur metric values remaining modules will be executed.

4.1. Limitation

From the proposed method, the blur information is important to recognize the forged region in the image. It is clear that when the image contains high degree of blur, the performance of the proposed method will decreases.

V. CONCLUSION AND FUTURE WORK

We have proposed a method for identifying forged blurred regions in the image. First, the proposed method introduces a new color texture features for segmenting region of interest irrespective of degree of blur and distortion effect. For each segmented region of interest, the proposed method estimates degree of blur by exploring blur metrics which involves study of variation of neighbor pixel information. This results in separating blurred regions irrespective of normal blurred regions and forged blurred regions. The blurred regions are yet to be validated by the new combination of Fourier coefficients based features and gradient features to identify the forged blurred regions based on similarity score between the regions. The similarities between the blurred regions must be estimated using Euclidean distance measure. Experimental results on standard datasets show that the proposed method is capable of detecting forged region under different situations.

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