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A FULLY AUTOMATED BLIND AND PASSIVE FORENSIC METHOD FOR IMAGE SPLICING DETECTION

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Abstract:— Well-known technique for image forgery is a splicing, in which a single composite image is formed with the help of two or more images. The aim of image splicing is to change the meaning and contents of an authentic image .The tampered images can be misused in many cases, some of which can be critical to an individual or organization. Hence, reliable detection of image splicing is of utmost importance. In the given paper, authors propose a fully automated, passive and blind method for image splicing detection. The proposed method use sensor noise features, which are obtained by Wavelet based denoising and various thresholding techniques such as hard and soft. The output of investigational images exhibit that the proposed method successfully detect and localized splicing with very less execution time in comparison to existing methods

Key Words: *Image splicing,Wavelet, Noise features, Hard Thresholding, Soft Thresholding;*

1. INTRODUCTION

The rapiddevelopments of commercial image editing tools and software such as GNU Image Manipulation Program (GIMP), Adobe Photoshop, haveextremely increased the amount of tampered images, which is circulating on social sites. Image tampering or image forgery has thus become a matter of concern because “Seeing is not believing” [32]. Tampering of images may be due to splicing, where a part of image does not belong to the original image, however,it has been taken from other images. Image forgery may be due to other reasons also, such as the darkening or lighting inconsistency [28] of skin tone, etc. Conventionally, image tampering detection was done by human inspection. Moreover, images may be digitally altered in many ways where the changes cannot be detected by the human eyes, thus the investigation of the image being tampered cannot be detected by human inspection. Therefore, there is a need for fast and robust-automated algorithms for the image tampering detection. Digital tampering detection is highly useful for business, newspapers, criminal forensics and finance to analyze forgery efficiently and accurately[29, 36].

Splicing technique combines image parts from the intra or inter images without further post-processing operation such as smoothing of boundaries among different parts of image. Let I(X, Y) and T(X, Y) are

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two images and t(x, y) is a part of T(X, Y) which is inserting into I(X, Y). Then, the generated spliced image S(X, Y) will be:

$$S(X, Y) = t(x, y) + I(x, y) \qquad (1)$$

Image forensic techniques fall in two categories:Active and Passive. Active forensic technique use pre-embedding information such as Digital Watermark[24,25] or Digital Signature, however passive forensic technique utilize intrinsic[23] information of image. In passive forensic technique, we can know the source of image but in passive and blind forensic technique [20], we do not know the source or origin of images.

Sensor noise introduced in the image during image acquisition process [21].Sensor noise features play important role in passive and blind image splicing detection. The various image denoising techniques were studied in the given paper with references[1,2,3,4,5,6,7,8,34].

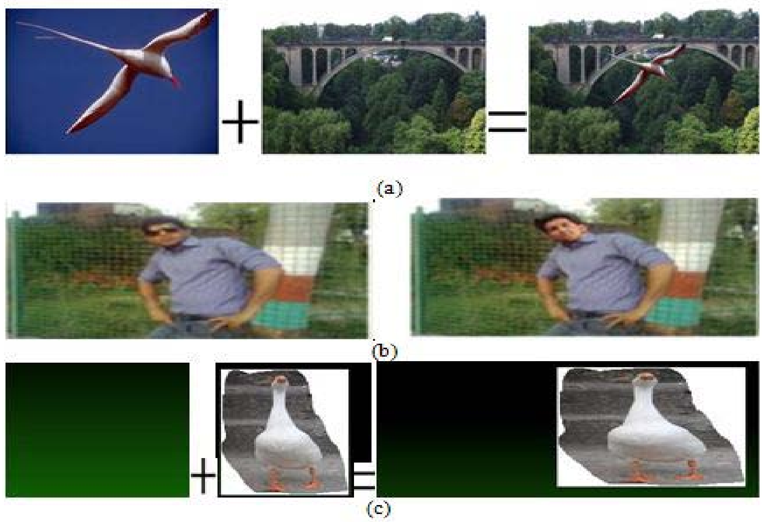


Fig.1.Example of spliced images

Image source and camera model identification using noisefeatures were presented by authors in their papers[10,11,12,13,14,15,16]. Image splicing detection using noise feature were discussed inreferences[17, 18, 19, 22, 26, 30,31,35,39,40]. Authors [1, 27,33]have presented various passive forensic techniques for images in respective survey paper.

In this paper, we are discussing passive-blind splicing detection method using Discrete Wavelet Transform (DWT) and different thresholding techniques and these techniques are providing commendable performance.

The contents of the proposed paper aredivided infour sections. In section II, we propose our method for image splicing detection. In section III, we provide the experimental results and discussion. In the last,section IV provides the conclusion and future works of image splicing detection.

2. THE PROPOSED METHOD

The proposed method is based on the variations of noise features for an image in the authentic and forged regions. Noise residue in different places of the authentic image regions will tend to be more similar while the noise residue between authentic and spliced regions is more likely to be different or distinct. These noise inconsistencies provides clue for image splicing detection and localization of spliced region. The proposed algorithm and pseudo code are as follow:

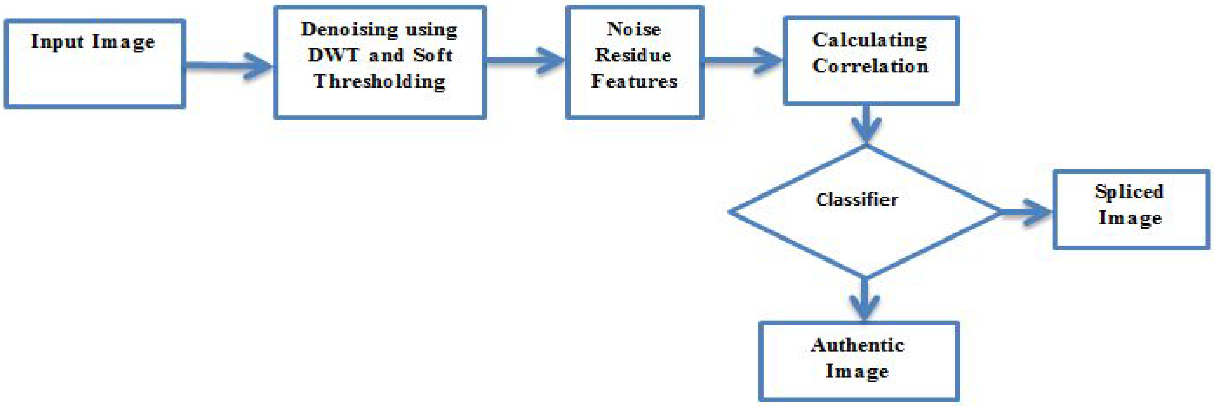


Fig.2Proposed method flow chart for splicing detection

2.1Algorithm

1. Take input image and convert to grayscale in order to obtain a single color channel matrix from the three-color channel matrix.
2. The image is then filtered, i.e., denoised by using DWT(Discrete Wavelet Transform). Denoising an image using DWT involves the following steps:
   - Apply wavelet transform to the input image. In this case, the Haar Wavelet Transform is used which divides an image of size $n \times n$ into four component images of size $n/2 \times n/2$.

A	H
V	D

A *(Approximation area):*It contains global information of an image.

H *(Horizontal area):*It contains information of vertical lines hidden in the image.

V *(Vertical area):*It contains information of horizontal lines hidden in image.

D *(Diagonal area):*It contains information of diagonal details hidden in an image.
These are calculated for each pixel (i, j) of the image as follows:

$$A = \frac{1}{2}[M(2i, 2j) + M(2i, 2j + 1) + M(2i + 1, 2j) + M(2i + 1, 2j + 1)]$$

$$H = \frac{1}{2}[M(2i,2j) - M(2i,2j+1) + M(2i+1,2j) - M(2i+1,2j+1)]$$

$$V = \frac{1}{2}[M(2i,2j) + M(2i,2j+1) - M(2i+1,2j) - M(2i+1,2j+1)]$$

$$D = \frac{1}{2}[M(2i,2j) - M(2i,2j+1) - M(2i+1,2j) + M(2i+1,2j+1)]$$

Use an appropriate threshold to remove noise. Thresholding used can be of two types:

- *Hard thresholding*

$$Thresh_{hard}\,[M(i,j)] = \begin{cases} M(i,j) & , \quad |M(i,j)| > T \\ 0 & , \quad |M(i,j)| \le T \end{cases}$$

- *Soft thresholding*

$$Thresh_{soft}\,[M(i,j)] = \begin{cases} sgn[M(i,j)]\{M(i,j) - T\} & , \quad |M(i,j)| > T \\ 0 & , \quad |M(i,j)| \le T \end{cases}$$

Soft thresholding provides more sophisticated results in comparison to hard, therefore it is preferred[37,38].Inverse wavelet transforms of the wavelet coefficients provides the denoised image. Inverse Haar Wavelet Transform can be calculated as follows:

$$M(2i,2j) = \frac{1}{2}[A + H + V + D]$$

$$M(2i,2j+1) = \frac{1}{2}[A - H + V - D]$$

$$M(2i+1,2j) = \frac{1}{2}[A + H - V - D]$$

$$M(2i+1,2j+1) = \frac{1}{2}[A - H - V + D]$$

3. Get the noise residue features by subtracting denoised image from original one.
4. The noise residuefeatures of images aredivided into blocks of 8×8 pixels and correlation is calculated amongst adjacent blocks of the image and stored in a correlation matrix. The correlation between two quantities x and y is calculated as follows:

$$corr(x,y) = \frac{covariance(x,y)}{\sigma_x \sigma_y} = \frac{E[(x - E(x))(y - E(y))]}{\sigma_x \sigma_y}$$

Whereσ_{exp} and $E(exp)$ denotes variance and mean respectively.

5. Finally,the Gaussian Mixture Density(GMD)based Bayesian classifier, classify the values of the correlation matrix and threshold of Bayesian classifier is set by Expectation Maximization algorithm [41].

6. The forged or spliced blocks are separately marked out in the output result.

2.2 Pseudo-code

Input image: img
detect_splicing(img)
{
convertToGrayscale(img);
haarWaveletTransform(img,haar_img);
Threshold(haar_img,soft threshold);
inverseHaarWaveletTransform(haar_img,denoise_img);
noise_residue=img-denoise_img;
calcCorrelationMatrix(noise_residue);
classify(corr_mat, EM_algorithm threshold);
return output_img;
}

3. EXPERIMENTAL RESULTS AND DISCUSSION

In this segment, we provide experimental results for the proposed method and demonstrate its performances. A dataset of 250 images is taken for the evaluation and analysis of the results. In the dataset images: 125 images are selected as first images and 125 images are selected as second one. The details of image resolution varies in the range 500 x 437 to1152 x 768 pixels but it is not fixed it may vary because we are considering any internet image. Table I provide the details of a few experimental images. The size of the spliced parts varies in the range 10-50% for the given images. According to requirements, the spliced parts of the images can be any shape such as rectangular, triangle, or other shape. Implementation of proposed method is performed using Open CV tools 2014.

The performance metrics of the method is measured in terms of True Positive Rate (TPR), False Positive Rate (FPR), and Accuracy.

TPR =Images detected as spliced being spliced / Total number of spliced images (1)

FPR =Images detected as spliced being original / Total number of original images (2)

$$Accuracy = \frac{N_{tp} + N_{tn}}{N_{tp} + N_{tn} + N_{fp} + N_{fn}} \tag{3}$$

Where, N_{tp} is the percentage of the spliced region detected as spliced; N_{tn} is the percentage of the authentic region detected as authentic; N_{fp} is the percentage of the spliced region detected as authentic; N_{fn} is the percentage of the authentic region detected as spliced.

The proposed method provides commendable performance using soft thresholding and Bayes shrinkage[38], which is shown in Table. II. We find very good result TPR95-98.5%, FPR 1-5% and accuracy 90-95%with theexperimental images, which have smooth and similar textured background. However, it does not provide good performance with different texture backgrounds. The gray scale images and noise residue features using soft thresholding are shown below in Fig.4A. Visual demonstration of experimental results is shown below in Fig.4B. The proposed method detects both single Fig. 4B (a, b, c) and multiple spliced regions Fig.4B.(d).Soft thresholding technique provides best results in comparison to hard thresholding and wiener filter Table II. The main advantages of proposed method is: It is fully automated means there is no manual interruption and it can detect image splicing of Internet images which sources is passive and blind. The execution time for image splicing detection in the four images (a, b, c, and d) with respect to their size is given in Table III. From Table III, we observe that execution time does not depend only to the size of image however, it also depend on the number of spliced region in the given image.Proposed method detects single and multi-region splicing with commendable speed and there is no substantial difference in execution time.When we compare the proposed method execution time with existing method then we get admirable performance that is shown in fig.3. Adaptive thresholding such as Bayes shrinkage provide better noise residue features and help to get more desirable result for splicing detection. To get the better result where compositions of spliced image have different textures, objects, and poor quality, we have requirement of huge number of spliced image for training to the GMD based Bayesian classifier. In this case, Adaptive thresholding perform exceptionally well and provide good result. The limitations of proposed method lie under the size, quality, classifier and noise extraction techniques of the image.

Table I. Details of a few spliced imagedataset

Image	File Type	Dimension	Resolution(dpi)	BitDepth	Compression
a	TIF	500*437	96	32	LZW
b	TIF	757*568	72	32	LZW
c	TIF	1152*768	72	32	LZW
d	TIF	569*437	96	32	LZW

Table II. Performance of image splicing detection

S. No	**Technique**	**TPR**	**FPR**	**Accuracy**
1.	Hard Thresholding	75-85%	10-15%	70-82%
2.	Wiener Filter	85-95%	5-10%	80-90%

3.	Soft Thresholding with Bayes Shrinkage	95-98.5%	1-5%	90-95%

Table III. Proposed method execution time

Images	Size(KB)	Execution Times (Second)
a	52.5	8.66
b	572	11.67
c	970	15.262
d	200	13.48

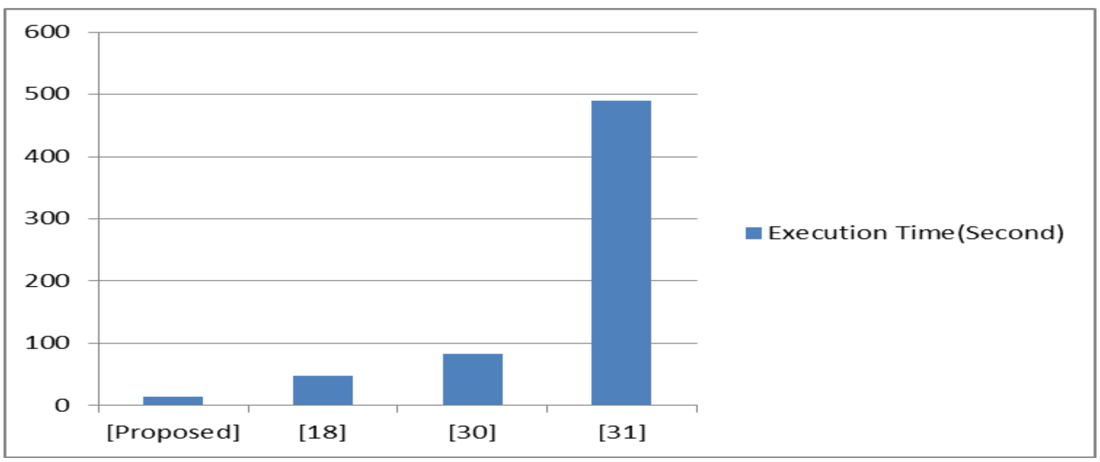
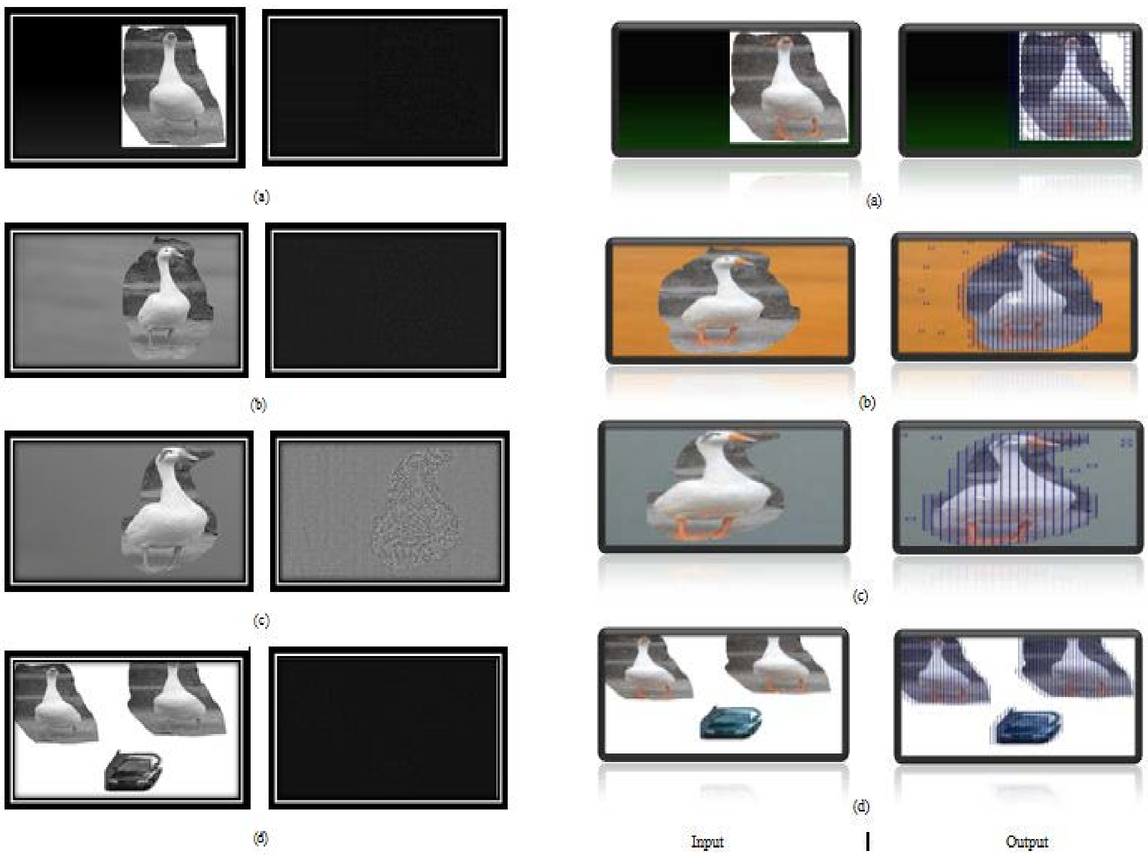


Fig.3. Execution time comparison for different methods



(A) (B)

Fig.4. (A) Gray images (Left) and noise residue features (Right) using Soft thresholding (B)Results of splicing detection (Left column show input composite images and right column show detected part of spliced images)

CONCLUSION

In this work, authors have demonstrated splicing detection method based on noise features and different thresholding techniques.Based on the results we have seen, Soft thresholding with Bayes shrinkage is providing a better result in comparison to Hard thresholding and Wiener filter. Proposed method is very fast in comparison to existing method because we are using fully automated technique for image splicing detection. In future, we want to detect splicing in human body and face, which we see on social sites such as Facebook or YouTube. Finally yet importantly, we want to detect real time splicing in the image using different image features.

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