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Splicing Localization Based on Noise Level Inconsistencies in Residuals of Color Channel Differences

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Abstract* : With the rapid usage of networking sites there is an enormous increase in image sharing over the internet. At the same time altering or tempering images has become much easier with the availability of photo editing software. Splicing is one of the tempering method, where an object from one image is copied and pasted into another image, is often used with the aim of either getting attention for fun or misleading the general masses. Thus, authenticity of images shared on internet is debatable. Active research is going on in the field of image forensics in order to examine the trustworthiness of the images. Amongst several techniques available for dealing with image splicing, the statistical based methods are gaining attention in research community as it uses image's local statistics. We propose a simple and effective method based on noise inconsistencies in residuals of Color channel difference for forensic analysis to localize the splicing image forgery. First the image is decomposed in to super pixels and extracted in regular shapes. From each super pixel, three color channel differences are extracted and noise level is estimated on the residual. Finally, the super pixels are clustered into two groups using Farthest Distributed Centroids Clustering (FDCC) method for classifying superpixel as tampered or original. The experimental results show the simplicity and effectiveness of the proposed method over the state of the art.

***Keywords* : Color Channel Differences, residual images, Superpixels, Splicing localization, Clustering.**

I. INTRODUCTION

In this digital era, everyone is fond of using the internet and social media which provides an aid to share ideas, images or videos. Not only that, digital images are widely used in the areas of journalism, medical imaging, and forensic investigation to provide evidence in the court of law to strengthen or disprove the complaints [1]. Moreover, everything depends on the veracity of the image.Surprisingly, the photo editing software's play a major role in altering the image content and people are altering the images either for fun or to put others into risk and/or spread misleading information, as shown in Figure 1. The news industry as well as the court of law investigations are the major places associated with the alterations of image content [2]. In both cases, there is a definite need to contribute towards developing efficient tools that can analyse the images and rate the trustworthiness of the image content.

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Image Forensics is the branch of Multimedia Forensics, where most of the researchers are focused towards investigating powerful tools for detecting any type of manipulation in the images [3]. Image tampering detection aims at verifying the authenticity of a digital images [4]. The authentication can be considered as active methods, where the authentication code embedded in the image would be verified with the original. Whereas, blind or passive methods make use of received image for assessing its authenticity without any external clues. In general, forged images do not leave any visual clues to indicate tampering but leave changes in its underlying statistics. The tampering may be either copy-move or splicing or resample.

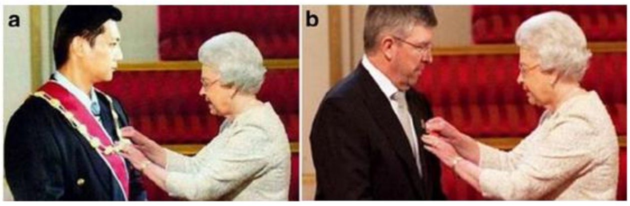

Fig.1 Image forgery Jeffrey Wong Su Receiving award from Queen Elizabeth-II [5]

Image splicing, a fundamental technique used in photomontage, where a region or object of an image is cropped and pasted in other image in such a way that it looks like as the original part of that image [6]. In the past, several feature-based techniques have been proposed for splicing image forgery detection. In all such methods, the effort is devoted to find a suitable statistical model to derive features for natural mages that gives highest discriminative power to detect the tampering such as copy-move or splicing [7]. Inspiring by the approach used in staganalysis [8], the image content does not help in detecting the local alterations, the features are derived based on co-occurrences matrices computed on the residual images. Because, the residual images are used to highlight more deviations from the typical appearance that occur during tampering of a natural image [9]. In general, to localize tempering it is assumed that the spliced region of the image is different from the whole image and is used as a fundamental aspect in localizing the forgery [10].

Due to the complexity of the image splicing localization problem, existing algorithms in the literature work either with an assumption by introducing specific operation in the spliced region or its edges like blurred edges, median filtered, resampled, contrast-enhanced and double JPEG compressed or based on intrinsic fingerprints of the original image such as Photo Response Non Uniformity (PRNU) which does not make any assumption but requires camera fingerprints to be available for forensic analysis. The noise based methods [11][12][13] are based on the fact that the intrinsic noise level is usually consistent across the whole image and used in splicing. Figure 2 shows two tampered images for image splicing. The left image consists of three butterflies with added noise spliced into another image. The added noise is due to discover the spliced region. The right image is directly taken from the Columbia spliced dataset [14] where the book is spliced into another image. Both images here are made from different cameras with different settings.

In [11], the noise is estimated as the local variance using wavelet-filtering and classified the spliced regions from the original image. The same applied for static scene video [15], where the authors estimated CRF of the frame and estimated the local variance and build a noise level function. In [16] image segmented into squared blocks and local noise is estimated based on positive kurtosis values in the band-pass domain. The Kurtosis concentration at the local level is used to detect the spliced segments. In [17], the researchers used SLIC segmentation and estimated the noise of each segment and a noise level function is estimated with the brightness and standard deviation of each segment in order to classify the spliced segments. They used multi-scale segmentation which works efficiently in classifying the segments as forged ones. There are algorithms that aim to localize both splicing and copy-move forgeries. [18] uses this idea where they created a special detector for each block combining JPEG block artificial grid with local noise discrepancies. The method seems to work effectively in both high quality and highly compressed images.

Fig.2 Examples of Image Splicing. (left) Three butterflies from another image with added noise spliced into the original image. (right) A book from another image is spliced into original image [14].

However, most of these methods work on block-based segmentation and assume a higher level of noise between the spliced object and original image in their experiments. Not only that they are sensitive to image texture, the rate of false positives consequently increases localization. Normally, the noise level difference is much smaller. These are the motivating factors for developing a simple method that can use superpixel segmentation and a small difference in noise levels.

In this paper, we propose an effective image splicing localization technique using noise level inconsistencies based on image statistics to effectively detect the areas of spliced regions. For the test image, we first segment into various regions based on superpixel segmentation and for each superpixel, we obtain a regular shape from neighbouring pixels and taken color channel differences RG, RB and BG. On each residual image we apply an efficient noise level estimation method to estimate the noise and merged all three noises as a feature vector. Using the simple FDCC algorithm to cluster the superpixels into two groups as original as well as the spliced. The experimental results show that the proposed method can localize the spliced regions more accurately than the state of the art.

The rest of the paper is organized as follows. Section II describes the proposed method for splicing localization, experimental results are described in Section III and finally, section IV gives the conclusions and scope for future work.

II. PROPOSED METHOD

In this work, the major focus is on localizing the spliced region in the tempered image. For the purpose of fine tuning splicing localization, the spliced image is first segmented using superpixels which divides the image into several non-overlapping superpixels based on similar colors, grey levels or pixel based. From each superpixel, the residuals RG, RB and GB are extracted from the color channels difference of RGB channels and the noise level is estimated on each residual to form the feature vector. Further to classify each superpixel as original or tempered, Farthest Distributed Centroids Clustering (FDCC) algorithm is used. The working principle of the proposed method is described in Figure 3 and 4.

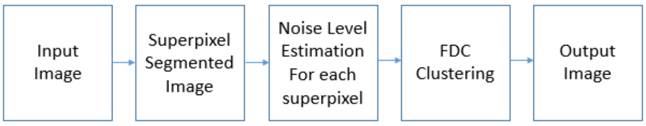

Fig. 3 Proposed working principle of Splicing forgery localization

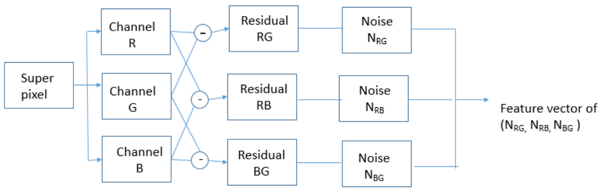

Fig. 4 Noise level estimation from each residual image

A. Residuals based Color Channel Differences

In the color image staganalysis the features are independently extracted from the residuals of each color channel, and then combined to form the feature vector in order to have better detection performance [19][20]. The steganalsis is in another way of tempering, taking advantage of it, we applied the residuals of color differences for splicing localization. First we extracted three color channels R, G, B from each superpixel and then obtained the residuals of channel differences RG, RB and GB. On each residual superpixel, we apply noise level estimation algorithm and combined standard deviations to form the feature vector (N_{RG}, N_{RB}, N_{GB}).

B. Noise level estimation of each superpixel

The major key point while applying any noise level estimation to image splicing regular shape from neighbouring pixels should separate the spliced region from original with exemplary accuracy for small blocks also. *Pyatykh* proposed a method of noise level estimation through principal component analysis, this method is one of the state-of-the-art for estimating noise level from single image. The major drawback of his approach is that it underestimate the noise level for processed images because of the smallest Eigenvalue of the covariance of selected low-rank patches as their noise estimation result. Considering these constraints, we choose an efficient noise level estimation method which uses the local image statistics [21 wherein the authors considered the observation that patches taken from pure images often lie in low-dimensional subspace, instead of being uniformly distributed across the ambient space. The low-dimensional subspace can be learned by the method of Principal Component Analysis (PCA) and the noise variance can be estimated from the Eigenvalues of redundant dimensions with the statistical property that the Eigen values of redundant dimensions are random variables following the same distribution. So, we employed this method to estimate the noise level estimation for each superpixel.

Let *J* be the noise-free image and *I* be the noisy image $I=J+n$ with additive white Gaussian noise *n* of size *M X N.*

The image *I* can be decomposed into a number of different patches $X_s = \{x_t\}_{t=1}^{s}$ each with patch size *d* X *d.*

For any arbitrary vector x_t in the set X_s, which can be decomposed as: $x_t = \widehat{x_t} + n_t$ where $\widehat{x_t}$ is corresponding to noise free image lying in low dimensional subspace and n_t is the additive Gaussian noise.

Since *I* is contaminated by Gaussian noise $n(0, \sigma^2)$ with zero-mean and variance σ^2, n_t follows a multivariate Gaussian distribution $N_r(0, \sigma^2 I)$ with mean 0 and covariance matrix $\sigma^2 I$.

From this, the noise level σ^2 of the dataset X_s get estimated.

The core idea is to obtain the accurate noise variance by removing the eigenvalues of principal components of the observed image *I* into the set of patches with dimensions S_1 from S.

The observed image *I* is first decomposed into a set of patches with size *d* and calculate the eigenvalues$S = \{\lambda_i\}_{i=1}^{r}$ of the decomposed dataset X_s.

Initialized with $S_1 = \emptyset$ and $S_2 = S$, the method proposed by [21] uses the difference between the mean μ and median ϕ of the subset S_2 to indicate whether there are outliers in the subset S_2 or not.

If $\mu \neq \phi$, the largest value in S_2 is taken out and put into the subset S_1.

This procedure will stop until the condition $\mu = \phi$ is reached and return the estimated noise as $\sigma = \sqrt{\phi}$.

For each superpixel of the residual image, this method is used for the estimation of noise variance.

Then all three noise varianes from each channel are merged as a feature vector.

C. Image Splicing localization

In order to identify the suspicious spliced region, the given test image is first segmented into superpixel segmentation using the state of the art method [22]. Then for each superpixel, the color channels are seperated and obtained the residual superpixels of channel differences. In color image steganalysis, the high-dimensional rich model features are extracted from the residuals of the channel differences [19]. On each residual image we applied high-pass filter to suppress the unnecessary values and the noise level is estimated. Instead of taking K superpixels as in all super pixel algorithms, method [22] takes super pixel width v_x and height v_y as inputs with an assumption that K can easily be obtained from them and vice versa. When the size of superpixel is larger fewer superpixels can be formed and is preferred for better noise level estimation. However since our aim is to localize the suspicious regions, the smaller size is also preferred. So, there is trade-off in selecting a size to make balance in accuracy and localization precision.

We preferred the superpixel size as 64 X 64 and obtained the superpixels. Since the superpixels are not regular in size, we used the method in [23] and fill the blank pixels with the original pixels of the image to make the superpixel into regular rectangular shape to make it convenient to estimate noise level using [21]. To get more precise localization of the spliced region with the size of the suspicious region is small, we used 32 X 32 size in order to reduce the false positive. Figure 5 shows Superpixel segmentation using 64 X 64 and gives 291 superpixels whereas with size 32 X 32 gives 1021 superpixels.

After the noise level of each superpixel is estimated, we used Farthest Distributed Centroids Clustering (FDCC) [24] algorithm to classify all superpixels into two clusters. The FDCC algorithm allows to make initial cluster centers and it acheives better quality clusters than the partitional clustering algorithm, agglomerative hierarchical clustering algorithm and the hierarchical partitioning clustering algorithm. Normally the clusters with fewer superpixels are the suspicious region, and we mark those superpixels. When the suspicious region is small as well as there are more suspicious regions, the size 64 X 64 leads to many false alarams. To improve this as a second step, we again segmented those superpixels with 32 X 32 and repeated the same method in order to fine-tune the localization.

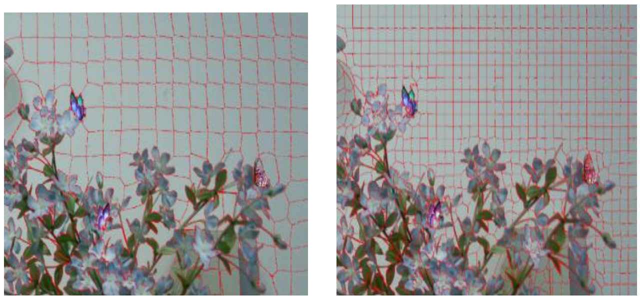

Figure 5: Superpixel segmentation using size 64 X 64 (left) and 32 X 32 (right) [22]

Algorithm 1 : Local Statistics based Splicing Forgery Localization

Input: Spliced Image

Output: Highlighted Suspicious Spliced Regions

Step 1: Split I into superpixels $I=S_j$, *where* $j= 1..N$

Step2: For each superpixel S_j, *where* $j= 1..N$:

a) Obtain a regular rectangular superpixel R_j
b) Obtain the three color channel superpixel J_R, J_G and J_B
c) Obtain the residuals J_{RG}, J_{RB}, J_{BG}.
d) Apply Highpass filter on each residutal

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e) Estimate the noise level of the residual and merge them to form featue vector $N(R_j)$

Step 3: Set initial clucster centers as min{ $N(R_j)$ } and max { $N(R_j)$}

Step 4: Clustering $N(R_j)$'s into C_k , Where k= {0, 1}

Step 4: Scan for the cluster with suspicious spliced object:X= C_k,Where k= 0 or 1

Step 5: Create a mask with $N(R_j)$ from X as a suspicious spliced region.

III. EXPERIMENTAL RESULTS

In this section, we present the experimental results of the proposed method for splicing localization and compare the results with the existing method where artificial noise is added in spliced regions of some standard dataset images.

A. Visual accuracy of splicing localization

We first compare the proposed method with the state-of-the-art noise based splicing localization method [13] on three spliced images created by *Abode Photoshop*. The dataset is collected from authentic images in Columbia dataset which are uncompressed and unprocessed TIFF images.

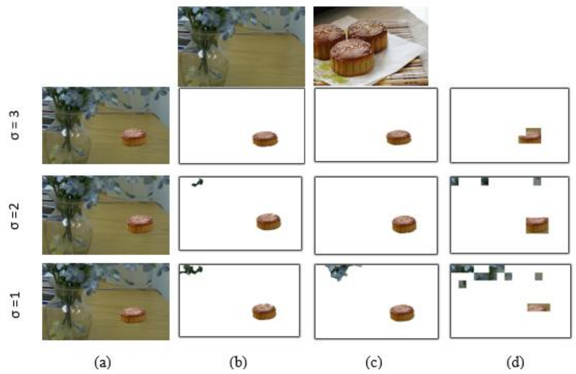

Fig. 6 Image Splicing with different added noise levels(σ=1,2,3) (a), detection results of the proposed method with superpixel size 32 X32 (b), with 64 X 64 (c) and the method {Formatting Citation} respectively. In b,c,d parts, only the suspicious regions are shown.

For the spliced regions, we added additive white Gaussian noise with standard deviation σ = 1, 2 and 3 and we did not considered more than that as it introduces visual artifacts which can easily be detected by human eye. Method [13] uses block-wise segmentation initially with block size 64 X 64 and then 32 X32 whereas the proposed method uses superpixel segmentation [18].

Figure 6 depicts an image splicing localization example in which one of the biscuits from another image is spliced into another image. The original images and image involved in spliced in splicing are shown in the top row and from the second row to the end,the left column (a) shows the spliced images with artificially added standard deviation respectively. The proposed method results are shown in (b) with size 32 X 32, (c) with size 64 X 64, and results for the method [13] shown in (d). The true positive and false positive segments are shown in the results. The true positive of the biscuit in full shape is detected in the proposed method where the method in[13] gives the clue about the forged region but because of regular segmentation, some of the segments are not shown whereas the proposed method able to capture the complete region of the spliced. When σ>=3 no false positives are shown in the proposed as well as method[13]whereas when σ=2,1 with superpixel size is 32X32, one segment showed falsely. Whereas the method [13] is unable to retrieve complete segments which are spliced along with many false positives found than the proposed method.

B. Robostness of splicing localization

Figure 7 shows another example of splicing localization in which more than one object with different noise levels is spliced into another image with different formats. First two rows are the results of TIFF format and the last two rows are the results of JPEG images.

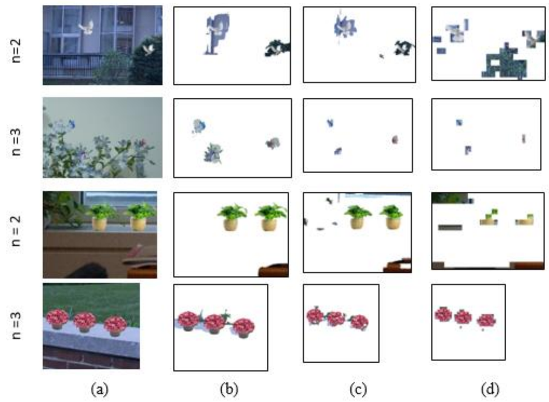

Fig.7 Image Splicing with different added noise levels (σ=1,2,3) with different no of spliced objects (n-2,3) with different formats TIFF,JPG (a), detection results of the proposed method with superpixel size 64 X64 (b), with 32 X 32 (c) and the method [13] respectively. In b,c,d only suspicious regions shown.

The first column (a) of all rows is the spliced image with n = 2 or 3 objects of another image spliced into an image. Columns (b), (c) are the results of the proposed method with size 64 X 64 and 32 X 32 and column (d) are the results of the method[13]. For the TIFF images, the proposed method results in false positives around the spliced region whereas the method in [13] gives more false positives. Whereas in JPEG images, the proposed method can capture the complete region along with some false positives whereas the method in [13] fail to capture all the segments involved in splicing.

C. Robostness with standard dataset

Finally, to get more realistic results, we compared our method to the method [13] with Columbia uncompressed Image Splicing detection evaluation dataset [25] directly without adding artificial noise. The authentic images are from the cameras - Canon G3, Nikon D70, and Nikon D70 and spliced with other cameras. Since the splicing takes with different cameras, there would be having different noise levels and we used that assumption to detect splicing. Four examples of the spliced images together with their detection results using both our proposed method and method [13] are presented in Figure 8.

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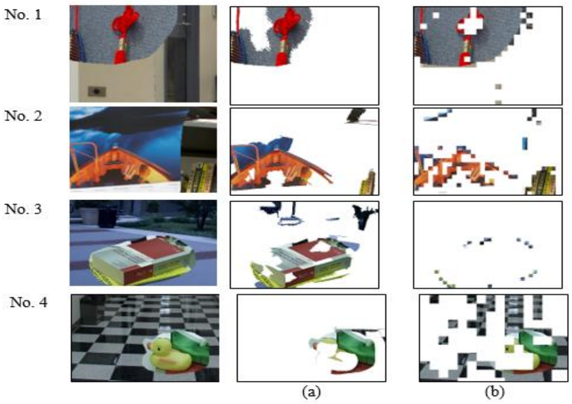

Fig. 8 Image splicing detection results from the Columbia uncompressed image splicing detection evaluation dataset (Yu-Feng Hsu 2007). (a) detection results of the proposed methodwith superpixel size 64 X64 (b) detection results of the method[13] with block size 32X32 respectively.

D. Detection Accuracy

We provided the pixel level detection accuracy in order to analyze the performance of the proposed method. For this purpose, we used True Positive Rate (TPR) and False Positive Rate (FPR) and F1 score as follows:

$$TPR = \frac{TP}{TP+FN} * 100\%$$

$$FPR = \frac{FP}{FP+TN} * 100\%$$

$$F1 = \frac{2*TP}{2*TP+FP+FN} * 100\%$$

Where TP is True Positive, FP is False Positive, TN is True Negative, FN is False Negative and TPR is the rate of pixels that are correctly detected as spliced in the region and FPR is the rate of pixels that are falsely detected as spliced in the region. Based on these F1 score is obtained.

Table1. Pixel-level performance comparison in '%' for the four test images from figure 8.

	Proposed method				method of Zang			
Image No	1	2	3	4	1	2	3	4
TPR	58.06	**70.69**	**68.18**	**60**	**68.18**	40.43	20.1	45.8
FPR	**0**	**8.16**	1.39	**1.99**	0.4	26.29	**0**	41.54
F1	73.47	**73.87**	**78.95**	**71.19**	**78.95**	37.88	33.47	29.48

From the results shown in the table 1 we concluded that the proposed method provides more accurate information than the method [13]. Both methods fail in some cases without detecting the segments. This is likely because the noise level difference of the original images and images involved in the splicing of this dataset is relatively very small and it is very difficult to distinguish than adding artificial noise.

We also collected 100 original image from BOSSbase dataset and added white Gaussian noise with standard deviation σ ranges from 1 to 5 to form 500 noise images. We cut small parts from the images and paste them into another original images thery by obtained around 1500 images as a dataset. We then perform the proposed method on each spliced image and compared with the method of Zang. The results are shown in Figure 9.

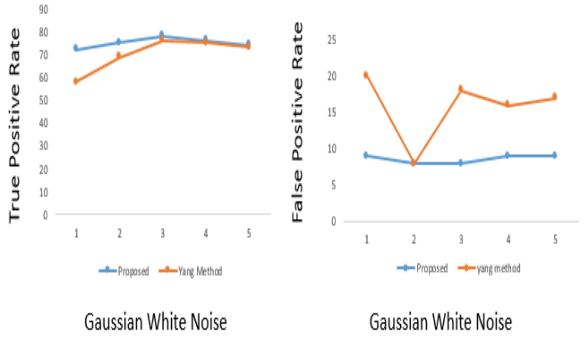

Figure 9: Comparion analysis of splicing detection accuracy. Left is TPR and right is FPR

From these results, it is proved that images from different sources tend to have different intrinsic noise level inconsistencies which can be used as a clue for image splicing localization. Whereas the noise–based methods may fail in some cases where there is no distinguishable difference in noise levels of the images involved in splicing. However, the proposed method outperforms some existing methods according to the experimental results.

IV. CONCLUSIONS

Driven by the question whether a given image segment is an original one or tampered, we proposed a simple and efficient image splicing localization method based on noise level inconsistencies in this paper. Our method is based on the assumption that the noise levels of the original image and image involved in splicing are different. We used superpixel segmentation instead of block-based segmentation which most of the techniques adopted. Since each superpixel is an irregular shape, we make each superpixelinto regular shape by taking the original pixel into consideration obtained residual superpixels from three color channel differences. On each residual superpixel we employed the state of the art efficient noise level estimation technique and estimated the noise level. After that, all superpixel are clustered into two using FDCC in order to classify the superpixels as original and spliced. The experimental results show that the proposed method outperforms in True positive rate as well as the false positive rate on the standard dataset images with the state of the art.In addition to the single object splicing, we also showed the reobostness of our method which can able to localize when there are more than one objects involved in splicing. The method also works not only with raw images but works on jpeg compressed image. Our future work involved to reduce the false positive rate when there are more than one objects involved and work with highly compressed and double compressed images.

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