International Journal of Engineering

Journal Homepage: www.ije.ir

Splicing Image Forgery Detection and Localization Based on Color Edge Inconsistency using Statistical Dispersion Measures

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P A P E R I N F O

Paper history:
Received 22 September 2020
Received in revised form 9 October 2020
Accepted 30 October 2020

Keywords:
Splicing Forgery Detection
Interquartile Range (IQR) Criterion
Contourlet Transform
Image Chroma
Image Segmentation

A B S T R A C T

Nowadays, due to the availability of low-cost and high-resolution digital cameras, and the rapid growth of user-friendly and advanced digital image processing tools, challenges for ensuring authenticity of digital images have been raised. Therefore, development of reliable image authenticity verification techniques has high importance in digital life. In this paper, we proposed a blind image splicing detection method based on color distribution in the neighborhood of edge pixels. First, we extracted edge pixels using contourlet transform. Then, to accurately distinguish the authentic edges from tampered ones, Interquartile Range (IQR) criteria are utilized to illustrate the distribution of Cr and Cr histograms of the spliced boundaries in YCbCr color space. Finally, a segmentation method is used to improve the localization performance and to reduce especially the computational time. The effectiveness of the method has been demonstrated by our experimental results obtained using the Columbia Image Splicing Detection Evaluation (CISED) dataset in terms of specificity and accuracy. It is observed that the proposed method outperforms some state-of-the-art methods. The detection accuracy is approximately 97 with 100% specificity.

doi: *10.5829/ije.2021.34.02b.16*

1. INTRODUCTION

In recent years, the rapid development of digital technology has emerged a great demand for forgery detection algorithms. Forgery detection methods can be mainly divided into two categories: active and passive methods [1]. Active methods are based on the procedure of embedding a kind of information in authentic image. Passive methods detect tampering in a given image without any prior knowledge of the authentic image. Passive methods, popularly known as blind methods, can be classified into copy-move (copy–paste or cloning) and splicing forgery detection categories [2, 3]. In copy-move methods, one or more parts of the authentic image are copied and pasted onto other parts of the same image. Therefore, the copied/pasted parts belong to the same image. Image splicing forgery detection method involves composition or merging of more than one image to produce a forged image.

Most of the existing copy-move and splicing forgery detection approaches use a three-major-steps procedure. First, they extract representative features from a given image; then, a suitable classifier is chosen and trained using the features. Finally, the trained model is used to classify given image into authentic and forged image category [1, 3-11].

Some prior works have suggested image splicing detection based on the Camera Response Function (CRF) abnormality [12], and CRF inconsistency [13] in different image regions of the tampered images. Image splicing detection based on run length is proposed in literture [14, 15]. According to He et al. [14], the edge gradient matrix of an image is computed, and followed by approximate run length calculation. High detection accuracy and low computational complexity with fewer features is claimed in this method. Attempts to model the tampered boundary can be frequently found in the splicing detection approaches [16]. Some image splicing

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Please cite this article as: M. Habibi, H. Hassanpour, Splicing Image Forgery Detection and Localization Based on Color Edge Inconsistency using Statistical Dispersion Measures, International Journal of Engineering, Transactions B: Applications Vol. 34, No. 02, (2021) 443-451

detection methods based on Hilbert-Huang transform (HHT) and moments of characteristic functions (CF) with wavelet decomposition (IQMs) are introduced. The presence of sharp changes between different regions and surrounding is valuable point in splicing image detection techniques [17].

Inconsistency at splicing boundaries is an important feature in splicing detection technique. Splicing detection based on color edge inconsistency were considered [18, 19]. A color image splicing detection technique based on a grey level co-occurrence matrix (GLCM) of edge image was outlined by Wang et al. [18]. They showed that the Chroma channel (Cb or Cr component)performs better thanYluminance component for detecting tampered edge pixels. So, the splicing edges would be detectable in Chroma channel [18]. Fang et al. [19] proposed a color image splicing detection method based on luminance. This method shows, in HSV color space, Hue histograms of tampered boundaries contain separated double peaks than histograms of Saturation or Value channel. Hue histogram entropy is used to label tampering boundaries.

The reminder of this paper is organized as follows. In section 2, a brief review on contourlet transform is presented. The contourlet transform is used to detect edge pixels carefully. Section 3 describes our proposed splicing detection method by considering inconsistency at tampering boundaries in YCbCr color space. The experimental results and our analysis are reported in section 4. The conclusion of this paper is presented in section 5.

2. The COBTOURLET TRANSFORM

Detection of edge with low error rate has dominant influence on splicing detection algorithms based on tampering boundaries. For this reason, in this paper we use the contourlet transform for splicing detection. The contourlet transform as an improvement for curvelet transform was introduced by Do and Vetterli [20]. The contourlet transform is a directional multi-resolution image representation that is used to show curves and fine details in the image. It also can describe lines and textures of images [21]. The directional multi-resolution representation contourlet takes advantages of the intrinsic geometrical structure of images, and is appropriate for the analysis of the image edges [22]. Figure 1 illustrates a comparison between the basic elements of wavelet and contourlet transforms near a smooth contour. In contourlet transform, the basic elements are oriented at a variety of directions with different aspect ratios [20, 23]. Therefore, it can successfully detect curves in images.

The authentic contourlet transform is a double filter bank structure. It is constructed as a combination of Laplacian pyramid (LP) and directional filter bank (DFB). The LP decomposes image into low pass and high pass sub-bands, iteratively [24]. Each high pass sub-band is then further decomposed by DFB to show directional information [25]. Therefore, the point discontinuities are identified by the LP. Then, a directional filter bank is used to connect these points into linear structure., The contourlet filter bank is shown in Figure 2 [26]. In contourlet transform, there are various directions at each scale, and the number of sub-bands can be determined by the user (see Figure 2).

3. PROPOSED METHOD

As mentioned earlier, we use contourlet transform to extract edges efficiently. First, we extract edges of test image as edge image. Then, further process is performed on the edge image to demonstrate tampered edge pixels. A simplified diagram of the proposed method is illustrated in Figure 3.

3. 1. Abnormality of Tampered Boundary in Color Space

In this section, for appropriately distinguishing authentic edges from tampered ones, we extract features from image edges in color space, especially in chroma channel. Since human eye is more sensitive to luminance than to chrominance [21], most of splicing detection technique only use luminance component of the color space [8]. Mahalakshmi et al. [8] incorporated the inconsistency of color distribution at splicing boundaries which was used to detect forgery in HSV color space, especially from H channel. One may convert RGB to YCbCr color space and apply the forgery method on YCbCr images [18, 27-29]. In this paper, we use YCbCr color space by extracting features from Cb and Cr components (chrominance) rather than Y (luminance). In Figure 4, the Y, Cb and Cr histograms of authentic and tampered edge pixels of an image are shown respectively.

(a) (b)

Figure 1. The basic elements located along smooth curves: (a) wavelet versus (b) contourlet transform [23]

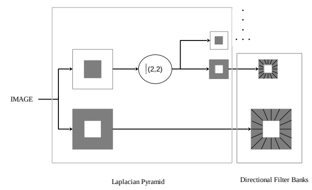


Figure 2. Contourlet filter bank (Pyramidal DFB). The point discontinuities are computed by the Laplacian Pyramid, and then linked into linear structure by Directional Filter Banks [26]

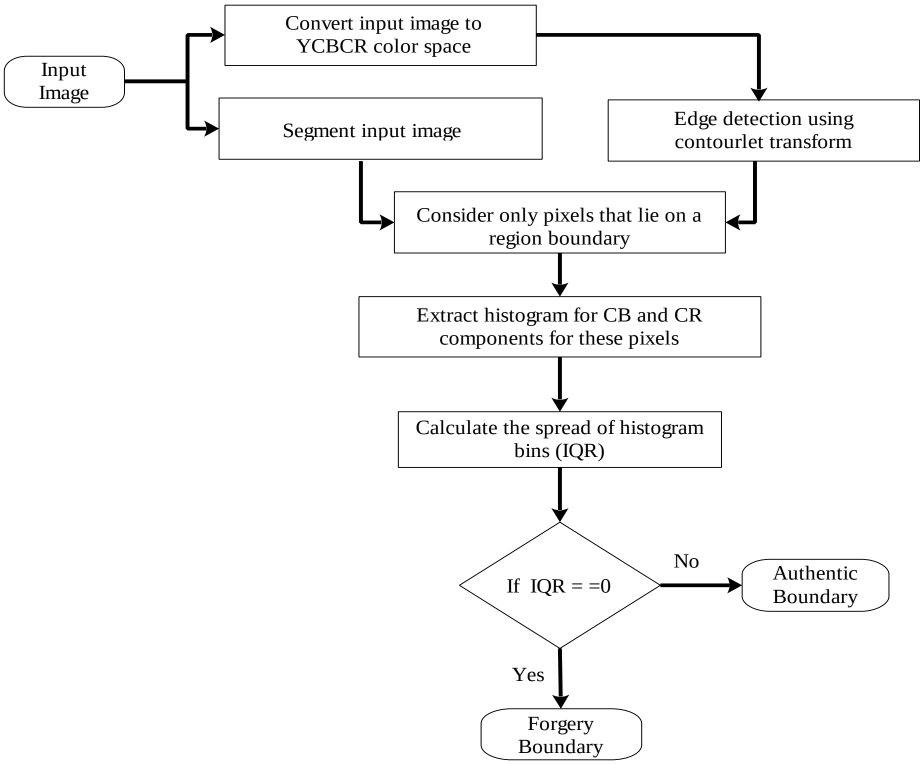
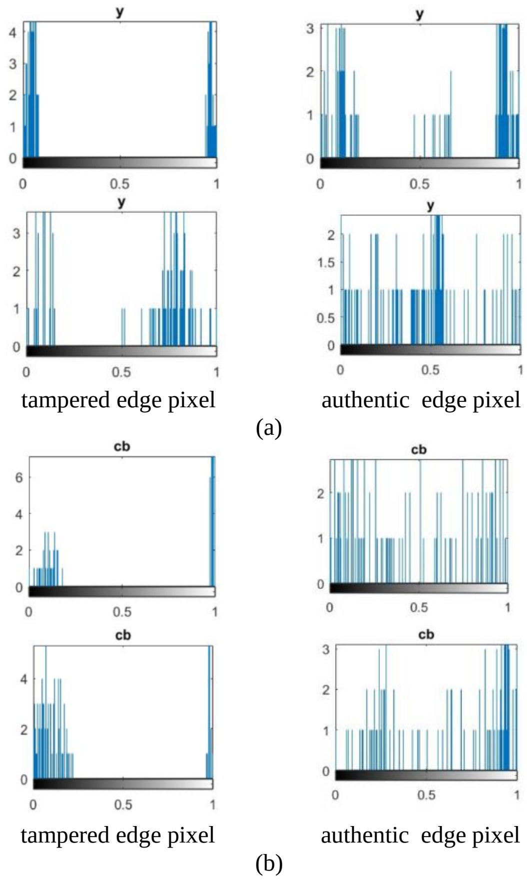


Figure 3. Flow chart of the proposed splicing image detection algorithm



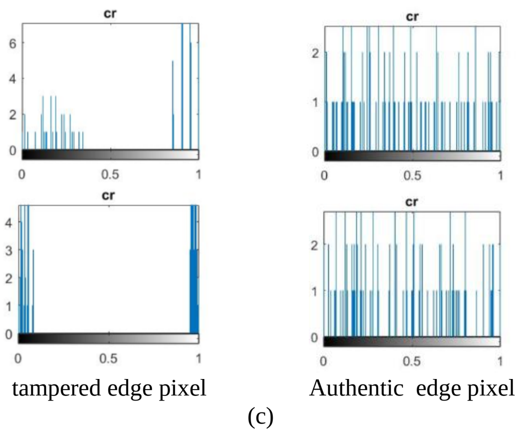


Figure 4. (a) Y component histograms, (b) Cb component histograms, and (c) Cr component histograms from two tampered (left) and authentic (right) edge pixels of an image

There is a little difference between the Y component histograms of tampered and authentic edge pixels, as shown in Figure 4(a). However, there are considerable differences between histograms of tampered and authentic edge pixel associated with the Cb and Cr components, as shown in Figures 4(b) and 4(c). In tampered edge pixels, the histogram values are left justified or right justified. In other words, the bins are empty in the middle for the Cb and Cr channels. For this end, the dispersion of histogram bins can be used to discriminate between the forgery and authentic edge pixels. After further investigation on the statistical dispersion criteria, we consider interquartile range (IQR) for splicing edge pixels detection. IQR divides the data set into four equal parts from Q1 to Q3 (Figure 5). Hence, in this paper, we used the distance between Q1 and Q3 to distinguish splicing edge pixel from authentic one (subsections 3.2). For tampered pixels, IQR of Cb and Cr histogram bins is zero.

3. 2. Interquartile Range Criterion As shown above, the histograms associated with the Cb and Cr of the tampered edge pixels have no value for the bins around the middle. The interquartile range, also called the mid-spread or H-spread,is a measure of statistical dispersion, based on dividing a data set into quartiles [30, 31]. Quartiles tell us about the spread of a data set by dividing the data set into four equal parts (quarters). The values that separate parts are denoted by Q1, Q2, and Q3, respectively, which are obtained using the following equation:

$$Q_i = \frac{i*N}{4} + \frac{1}{2} \quad (1)$$

where Q_i is the i^{th} quartile (for $i = 1,3$) and N is the number of histogram bins.

The box shows the interquartile range (the distance between Q1 and Q3), as shown in Figure 5.

The IQR of a set of values is calculated by subtracting the first quartile (Q1) from the third quartile (Q3). The interquartile range is computed using the following equation:

$$IQR = Q_3 - Q_1 \quad (2)$$

For all edge pixels in edge image, IQR of Cb and Cr histogram bins are calculated. Then, each edge pixel with IQR equal to zero is labeled as tampered pixel.

3. 3. Improving the Splicing Detection Method by Segmentation Algorithm The proposed method in this paper considers splicing edge pixels from the image for forgery detection. Hence, edge pixels are extracted in a pre-processing step. Indeed, the input image is initially segmented, then, the border pixels of the segmented regions will be further processed. The pre-processing step slightly improves accuracy of the forgery detection and significantly reduces the execution time for forgery detection. After testing image segmentation methods [32-34], it is observed that the segmentation method does not significantly influence the proposed method's performance. We choose segmentation algorithm for pre-processing stage that is described by Nock et al. [33].

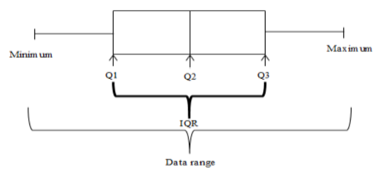


Figure 5. The interquartile range ($IQR = Q_3 - Q_1$)

4. EXPERIMENTAL RESULTS

To demonstrate effectiveness of the proposed approach, experimental results are presented in this section. We have evaluated our proposed approach with a series of experiments. We used the Columbia Image Splicing Detection Evaluation Dataset (CISED) for the experiments [35], which is a benchmark for image splicing detection algorithms. The database contains 183 authentic and 180 tampered color images of sizes range from 757×568 to 1002×66.

The tampered images were constructed from the authentic images. In this dataset, for each tampered image, there is one image that identified as 'edgemask' image. Hence, we use the edgemask image to evaluate our proposed method. The experiments were performed using the MATLAB (R2018b) tools on PC environment (the 64-bit version of Windows 10, Intel® core™ i7-4710HQ CPU, 2.50GHz and 8GB RAM). Figure 6 shows the results of the proposed method for two metrics: variance and the interquartile range. In Figures 6(b) and 6(c), the white pixels indicate the splicing boundary.

The second experiment is performed to test the effect of the segmentation algorithm on our method. By using the segmentation algorithm for preprocessing, the number of pixels are decreased for processing.

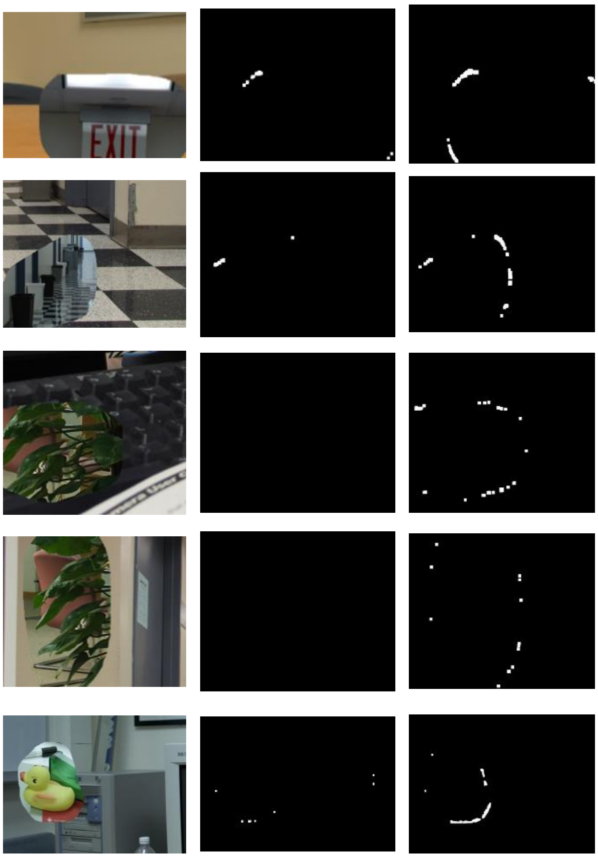
Therefore, our method reduces the computational complexity. Time consuming of our proposed approach with segmentation algorithm as preprocessing method for the images shown in Figure 7 is summarized in Table 1.

As seen above, by applying segmentation algorithm, not only the spliced boundaries are detected accurately, but also the time of our approach is decreased obviously, as can be seen in Figure 6 and Table 1. For further comparison, the average run-time of the proposed approach and some methods on CISED dataset are listed in Table 2.

In Table 2, it can be seen that our proposed method is better than the others.

The average time of the proposed approach by using segmentation algorithm is reduced by approximately one third, as shown in Table 2. Since we claim that our method with pre-processing step dramatically reduces the computation time, the time of our method with and without pre-processing step for each image in CISED dataset are shown in Figure 8.

For evaluation of the performance of the proposed method, we demonstrate a detailed analysis of the proposed approach based on evaluation metrics such



(a) (b) (c)

Figure 6. The sample results of the proposed method. (a) spliced image (b) variance metric (c) IQR metric

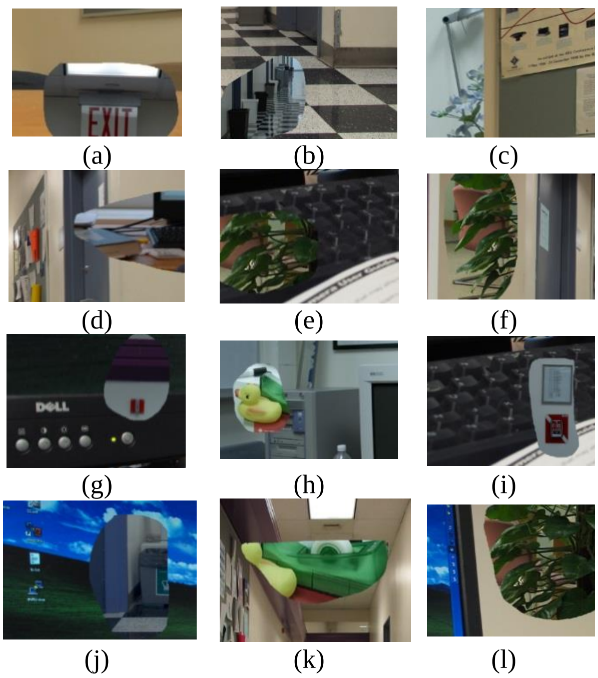


Figure 7. Some example splicing images of the CISED dataset (used in Table 1)

TABLE 1. Time cost of our proposed method by considering segmentation time (s)

Method Image	Our method (without segmentation)	Our method (with segmentation)
Figure 7.a	551	154
Figure 7.b	699	223
Figure 7.c	118	91
Figure 7.d	369	159
Figure 7.e	1424	244
Figure 7.f	515	180
Figure 7.g	931	89
Figure 7.h	277	176
Figure 7.i	1018	217
Figure 7.j	128	27
Figure 7.k	248	136
Figure 7.l	615	174

as specificity and accuracy by Equations (3) and (4).

$$Specificity\ (TNR) = \frac{TN}{TN+FP} \quad (3)$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (4)$$

where TP (True Positive) is the number of spliced pixels which are detected correctly as spliced, FP (False Positive) is the number of authentic pixels which are detected wrongly as spliced, TN (True Negative) is the number of authentic pixels which are correctly detected as authentic and FN (False Negative) is the number of spliced pixels which are wrongly detected as authentic. In Figures 9(a) and 9(b), the specificity and accuracy rate of the proposed method with and without pre-processing step for each image in CISED dataset are shown, respectively.

In CISED dataset, the size of images changes from 757×568 to 1002×66. Hence, this is reason for increasing computation time at the right-hand side of the graph (Figure 8).

TABLE 2. Comparison of run time of various methods on CISED dataset

Methods	Running time (s)
Le-Tien[36] (input-450)	308.76
Le-Tien[36] (input-300)	243.75
Huh et. al.[37]	212.64
Xiao et. al.[38](patch-level CNN)	375.76
Our method (without segmentation)	573.72
Our method (with segmentation)	211.93

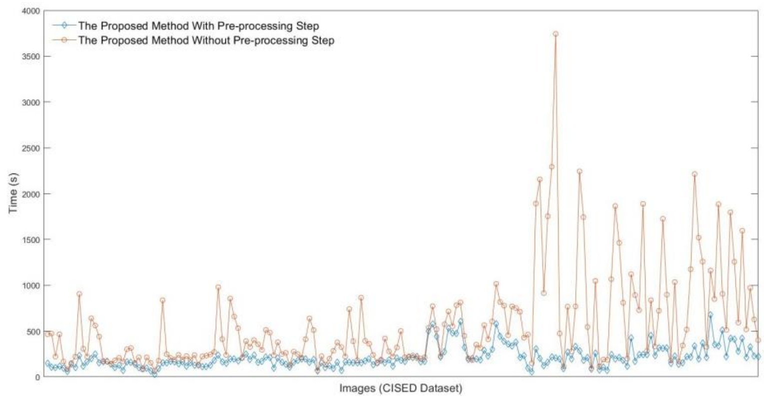
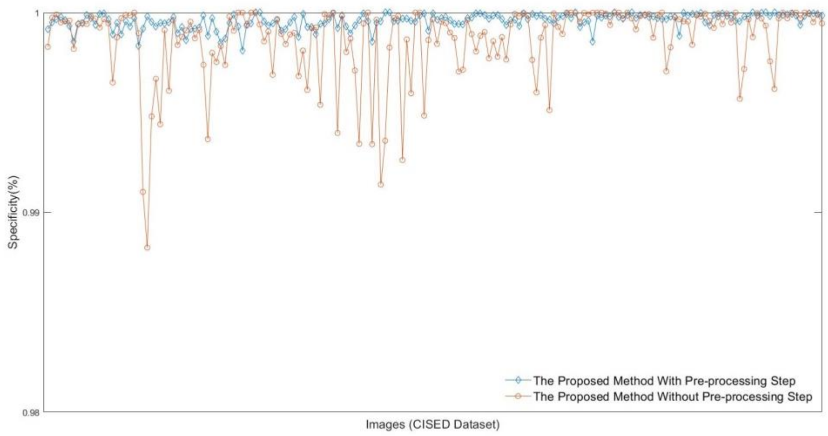
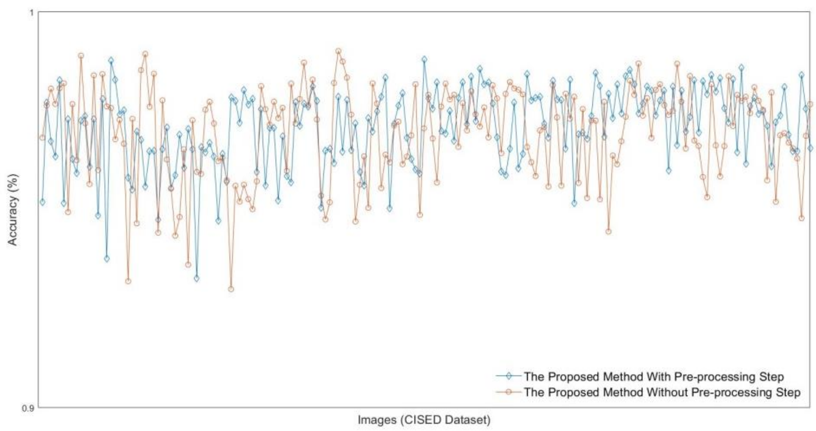


Figure 8. Comparisons time of the proposed approach with (blue solid line with diamond markers) and without (red solid line with circle markers) pre-processing step for each image in CISED dataset



(a)



(b)

Figure 9. Comparisons (a) the specificity rate and (b) the accuracy rate of the proposed approach with (blue solid line with diamond markers) and without (red solid line with circle markers) pre-processing step for each image in CISED dataset

To evaluate the performance of our proposed method, the specificity and accuracy rate of our approach and other methods on CISED dataset is illustrated in Table 3. It is clearly seen that the proposed method performs better than some state-of-the-art methods.

According to the results summarized in Table 3, the specificity and accuracy rate of the proposed method are 99.96 and 97.08, on the CISED dataset, respectively. The proposed method has better accuracy rate compared to other methods except the methods proposed by Abrahim et al. [39], and Jaiswal and Srivastava [40]; but the proposed method has the highest specificity rate.

In Figure 10, the bar graph represents the comparative result of our method with other state-of-the-art methods.

TABLE 3. The comparison of the proposed method with other detection methods in terms of detection accuracy and specificity rate on CISED dataset.

Methods	Specificity	Accuracy
Muhammad et al. [6]	95.53	96.39
Zhang and Zhao [41]	-	91.38
He and Lu [42]	94.32	93.55
Agarwal et. al. [43]	88.63	91.14
Saleh et. al. [44]	-	94.17
Zhao et al. [45]	-	93.14
Jaiswal and Srivastava [40]	98.58	98.80
Park et. al. [46]	-	94.80
Han et. al. [47]	94.58	92.89
Rao et. al.[48]	-	96.38
Zhao et. al [49]	93.75	93.36
Abrahim et. al.[39]	96.07	**99.43**
Huh et. al.[37]	-	87.00
Zhang et. al.[50]	95.33	94.10
Pomari et. al [51]	-	96.00
Our method (without segmentation)	99.86	96.94
Our method (with segmentation)	**99.96**	97.08

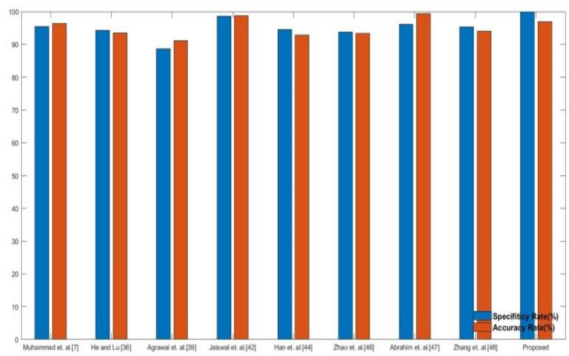


Figure 10. Specificity (blue) and Accuracy (orange) rate of our method and comparative methods

5. CONCLUSIONS

In this paper, we have proposed a splicing image detection approach based on color distribution of edge pixels in chroma space. At the initial stage, the input image is converted to YCbCr space. Next, edge image is extracted using contourlet transform. Finally, for each edge pixel, we use IQR metric of the Cb and Cr histogram bins to distinguish between the tampered and authentic edge pixels. In order to dramatically decrease the computational time and also improve the localization performance, the segmentation algorithm is used for pre-processing stage. Experimental results demonstrate that our proposed method outperforms all comparative the state-of-the-art methods on computational time and specificity rate. We can see the specificity and accuracy of our method are approximately to 100 and 97% on the CISED dataset, respectively.

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Persian Abstract

چکیده

در سال‌های اخیر، دوربین‌های دیجیتال با تفکیک‌پذیری بالا و قیمت پائین می‌توانند در دسترس همگی قرار گیرند. از طرف دیگر، در زمینه پردازش تصاویر دیجیتالی، ابزارهای قدرتمند و کاربرپسند به سرعت توسعه می‌یابند. این عوامل باعث شده است که چالش‌هایی برای اطمینان از صحت تصاویر بدست آمده، به وجود آید. لذا، توسعه روش هایی برای تایید اعتبار یک تصویر، نقش به سزایی در زندگی دیجیتالی امروزی دارد. در این مقاله، یک روش تشخیص جعل بر اساس توزیع رنگ در همسایگی پیکسل های لبه پیشنهاد می‌شود. ابتدا، پیکسل‌های لبه با استفاده از تبدیل کونتورلت استخراج می‌شوند. سپس، به ازای هر پیکسل لبه، پیکسل‌های همسایگی آن نیز در نظر گرفته شده و هیستوگرام مولفه‌های Cb و Cr از فضای رنگ YCbCr ترسیم می‌شود. در این مقاله، برای شناسایی پیکسل جعلی از پیکسل واقعی، از معیار دامنه چارکی (IQR) برای تعیین نحوه توزیع میله‌های هیستوگرام‌های Cb و Cr استفاده می‌شود. در نهایت، برای کاهش زمان محاسباتی و افزایش دقت روش پیشنهادی در تشخیص مکان جعل، از الگوریتم فطعه‌بندی به‌عنوان یک گام پیش پردازش استفاده می‌شود. دو معیار accuracy و specificity، برای ارزیابی میزان کارایی روش پیشنهادی مورد استفاده قرار می‌گیرد. نتایج اعمال روش پیشنهادی بر پایگاه تصاویر CISED نشان می‌دهد که روش پیشنهادی بهتر از روش‌های مطرح در این زمینه عمل کرده است و accuracy و specificity روش پیشنهادی به ترتیب ۹۷ درصد و نزدیک ۱۰۰ درصد است.