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Multi-Phased Feature Extraction And Adaptive Thresholding For Pixel-Wise Localization Of Tampered Regions In An Image Using ELA Based Analysis

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Abstract: The advancement in artificial intelligence (AI), advanced image processing software empowers users with a vast array of editing tools, significantly altering how we interact with visual content. However, these advancements also present significant security concerns, especially regarding the spread of fake images on digital platforms. Combating image manipulation has become crucial in information security and multimedia applications. This paper addresses this critical issue by examining two main categories of image forgery: computer-generated content manipulation and deepfakes, with a focus on the common technique of splicing/compositing images from various sources. We explore recent developments in detection and localization methods, including analyzing inconsistencies in Colour Filter Array (CFA) patterns, noise levels, and JPEG compression variations. While deep learning approaches are gaining traction, traditional computer graphics-based methods remain valuable due to their reliability. The paper identifies three key challenges in combating image manipulation: efficient feature extraction, reducing reliance on manual parameter selection, and ensuring comprehensive identification of tampered areas. To address these challenges, we propose a novel approach using Contrast Limited Adaptive Histogram Equalization (CLAHE) that leverages noise artifacts and Error Level Analysis (ELA) weighted features to improve the visibility of manipulated regions. Our contributions include a multi-phase feature enhancement technique, a Contrast-based Adaptive Histogram Equalization method, and an Adaptive threshold-based pixel-wise localization method. These methods offer promising avenues for robust tampering detection across various digital platforms.

***Index Terms* -** ELA weight feature, Adaptive threshold, pixel-wise localization, Contrast based Adaptive Histogram Equivalization.

I. Introduction

The advancement of artificial intelligence (AI) has led to the rise of sophisticated image processing software, offering users a diverse array of capabilities. This technological progression has revolutionized the way people engage with images, presenting them with unparalleled opportunities for creativity and entertainment. However, this innovation has also introduced significant security concerns. The proliferation of counterfeit images across various platforms, including social media, internet technology and news media, poses a profound threat to the integrity and reliability of visual content. Consequently, combating the pervasive issue of image manipulation has emerged as a crucial area of focus within the realms of information security and multimedia applications

There exist predominantly two categories of image forgery: computer graphics-based content manipulation and deep fake technology. The former encompasses a variety of methods including heterogeneous image splicing/compositing, copy-move manipulation of homogenous images, and localized attribute alterations. Among these techniques, heterogeneous image splicing/compositing stands out as the most prevalent form of image tampering due to its extensive applicability. This technique involves selectively copying sections of one or multiple source images and integrating them seamlessly into a target image to fabricate scenes that are entirely synthetic.

In recent times, a plethora of detection and localization techniques have emerged to combat such tampering attacks. These methods encompass a variety of approaches, including the identification of inconsistencies in Colour Filter Array (CFA) interpolation patterns (Zhang, Fang, and Zhang, 2015; Fernández, Orozco, and Villalba, 2023), disparities in noise levels (Peng and Kang, 2016), variations in JPEG compression quality (Jeronymo, Borges, and dos Santos Coelho, 2017; Bianchi and Piva, 2011, 2012), alongside other innovative strategies (Mehta et al., 2021; Yıldırım and Ulutaş, 2019). Despite the emergence of deep learning-based detection methods driven by advancements in artificial intelligence technology, traditional computer graphics-based methods persist as invaluable assets due to their reliability. These methods typically involve two stages: a detection phase, which entails feature extraction for preliminary forgery trace identification, and a tampered region localization phase, employing techniques like classification, clustering, and segmentation to pinpoint and delineate the altered areas. While some approaches rely on manually set average thresholds for forensic features, potentially leading to inaccuracies in localization and higher false detection rates, others strive to refine localization through various means, albeit often at the cost of increased computational complexity and time.

To tackle these challenges, we must address three critical issues: (1) how to effectively extract salient features from tampered regions within images to facilitate automatic detection while minimizing false positives; (2) how to mitigate reliance on manual parameter selection and reduce the impact of subjective factors; (3) how to ensure the highlighting of tampered regions regardless of their location within the image. In this research, we concentrate on these concerns and propose a novel approach leveraging Contrast Limited Adaptive Histogram Equalization (CLAHE) for detecting and localizing tampered regions. Our method introduces two distinct features: the noise artifact feature, which captures local noise distribution inconsistencies, and the Error Level Analysis (ELA) weighted feature, emphasizing disparities in image compression quality, particularly along edges and texture-rich areas. By leveraging these features, we employ an adaptive histogram equalization algorithm to enhance the visibility of tampered regions. Through pixel-wise localization and an adaptive threshold mechanism, we effectively highlight tampered areas irrespective of their placement within the image. Notably, our method boasts minimal parameters and high computational efficiency compared to existing approaches. Experimental results demonstrate its robustness against various attacks, indicating its suitability for detecting manipulated images across platforms such as WhatsApp, Instagram, and Facebook.

II. RELATED WORK

Revealing the authenticity of the image content in the absence of any prior knowledge poses a serious challenge. Early methods could only detect the authenticity of an image but not locate spliced regions. Recently, many effective methods for spliced region localization have emerged. Based on the principles of feature extraction, these methods can be mainly classified into JPEG compression-based methods, noise-based methods, CFA-based methods and others. Considering the potential variations in levels of JPEG compression experienced by different images, the JPEG compression effect can be used as an effective tool to detect image splicing. Xue et al. (Xue, Lu, Ye and Liu, 2019) proposed a method that uses the Normalized Gray Level Co-occurrence Matrix (NGLCM) to estimate the posterior probability of the discrete Cosine Transform (DCT) coefficients of each image patch to generate a probability map and thus identify the splicing region. However, this method is only effective when the JPEG compression factor of the original region is smaller than that of the spliced region. Mire et al. (Mire, Dhok, Mistry and Porey, 2018) proposed an image splicing detection method that does not rely on prior knowledge of the JPEG compression factor. They calculated the probability distribution of the first digit of the first 20 AC coefficients for both the test image and its Gaussian version. Using the K-means clustering algorithm, they localized the spliced region, offering an advantage over previous methods. Iakovidou et al. (Iakovidou, Zampoglou, Papadopoulos and Kompatsiaris, 2018) presented a technique for detecting tampering in JPEG format images, identifying anomalies in grid alignment and suspicious tampered regions through assessing estimated values in different grid regions. Niu et al. (Niu, Tondi, Zhao, Ni and Barni, 2021) introduced a spliced image localization algorithm based on inconsistencies in JPEG recompression, involving clustering image blocks using estimated primary quantization matrices and subsequent refinement through morphological operations. In summary, Most of the JPEG compression-based image splicing detection methods can detect the tampered regions. However, the effectiveness of these methods may be limited in identifying highly concealed tampered regions, leading to less robustness for content-preserving manipulation or degraded images. The composite image typically exhibits varying noise levels since the spliced regions are usually sourced from different images. Hence, inconsistency in noise levels serves as a reliable indicator for detecting image tampering. Lyn et al. (Lyu, Pan and Zhang, 2014) introduced a method for locating spliced image regions by detecting local noise level inconsistencies. Zhang et al. (Zhang, Wang, Zhang and Hu, 2019) introduced a tampering localization method. In this work, authors estimate the noise level and feature distribution of image blocks that are segmented by super-pixels to construct identification features, and fuzzy C-means clustering is employed for the localization process. Chen et al. (Chen, Retraint and Qiao, 2022) introduced a simplified noise model detector under the assumption that pixel variance follows a quadratic function of pixel expectation. Experimental results substantiated the validity of this model. Liu et al. (Liu and Pun, 2020) proposed a splicing region localization method that utilizes adaptive singular value decomposition to estimate local noise and constructs a neighborhood noise descriptor containing both global and local noise information. This method can detect multiple target regions from different sources, enhancing the performance of image splicing region localization. In general, noise level inconsistency-based image splicing detection methods are all able to identify tampered regions. However, the noteworthy aspect is that the degraded image will impair the detection performance of these methods. Since spliced regions in images often originate from different images that captured by different cameras with different CFA patterns, the inconsistency in the CFA interpolation pattern can serve as evidence for image splicing detection. A classical approach was introduced by Popescu and Farid (Popescu and Farid, 2005), which employed a maximum expectation algorithm and a linear model. Singh et al. (Singh and Singh, 2020) proposed a method employing a Markov transfer probability matrix (MTPM) for higher-order statistical analysis, demonstrating higher efficiency but with mis detected regions. Wang et al. (Wang, Niu and Zhang, 2020) presented an image splicing detection algorithm based on dual cubic interpolation and Gaussian mixture models. This algorithm extracts image features to identify and locate tampered regions by analyzing the variance of prediction errors in the CFA interpolation model. Liu et al. (Liu, Sun, Lang, Li and Shi, 2022) utilized dual-tree wavelet transform to extract single-channel CFA interpolation and pixel noise, using the ratio of pixel noise levels for forged region localization. Wang et al. (Wang, Wang, Lei, Li, Wang and Xue, 2022) employed a coarse-to-fine granularity approach for CFA-based tampering region localization. In general, these methods can detect tampered regions. However, these methods are not robust for JPEG compression that destroys the CFA interpolation artifact. In recent years, the application of deep learning in image splicing detection has gained significant traction, leading to the emergence of numerous exceptional methodologies. Xiao et al. (Xiao, Wei, Bi, Li and Ma, 2020) proposed a two-phase CNN-based algorithm that utilizes CNNs of different scales to extract attribute differences, generating the final forged region through adaptive clustering. Huang et al. (Huang, Bian, Li, Wang and Li, 2022) introduced a two-stream network for detection and localization, using an RGB stream for coarse localization and a noise stream for fine localization, gradually refining predictions with a decoder. Dong et al. (Dong, Chen, Hu, Cao and Li, 2022) developed MVSS-net, a multi-view and multi-scale method, extracting noise and edge information separately for high pixel-level localization accuracy. Kwon et al. (Kwon, Yu, Nam and Lee, 2021) presented a method combining forensic features and regression analysis for spliced region localization, demonstrating efficient and robust detection. In conclusion, although deep learning-based methods can effectively detect manipulated regions, they require a large amount of labeled data and high-performance computing, which poses challenges for real-world applications.

III. OBJECTIVE

The main contributions of this study are as follows.

- A multi-phase feature enhancement technique is defined by combining the noise artifact feature and ELA weighted feature to make the tampered regions stand out in an image.
- A Contrast-based Adaptive Histogram Equalization method is used to enhance the visibility of the tampered regions which were not sensitive to the former feature extractions.
- An Adaptive threshold-based pixel-wise localization method is leveraged to highlight the tampered regions regardless of any regions in an image.

IV. RESEARCH METHODOLOGY

4.1. PROPOSED METHOD

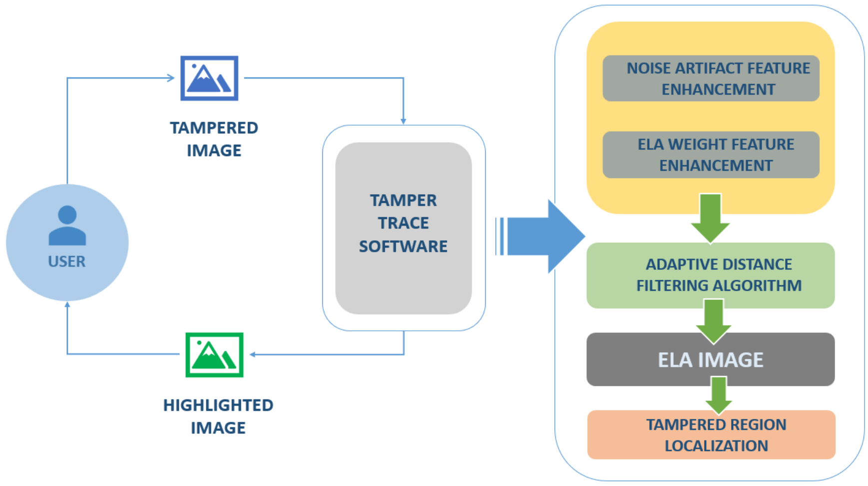

Figure 1: Framework of the proposed method.

In the proposed system, a comprehensive approach is utilized for image tampering detection and localization, focusing on enhancing image features to accurately identify tampered regions. To achieve this, a multi-phased feature enhancement strategy is employed, targeting both noise artifact and Error Level Analysis (ELA) weight features. Firstly, the noise artifact feature is enhanced, crucial for identifying tampered regions distinct from authentic image regions. This enhancement involves decomposing the image into its RGB channels and applying discrete wavelet transform followed by a median filter to extract noise features. Subsequently, Laplacian of Gaussian (LOG) operators are utilized to highlight salient features caused by noise, creating saliency images. Finally, the maximum values of the noise and saliency images are combined to generate the noise artifact feature. This feature enhancement method effectively identifies splicing regions across diverse datasets. Secondly, focus is placed on enhancing the ELA weighted feature, leveraging the ELA method to identify discrepancies in JPEG compression levels within an image. This process involves compressing the image at a 90% rate and comparing it with the original to extract differential features. These features are decomposed into RGB channels, and a weighted sum is computed to generate the ELA weighted feature. Notably, the weighting scheme accounts for the typical 1:2:1 ratio of red, green, and blue pixels in colour photographs, ensuring balanced feature representation. The resulting ELA weighted feature offers valuable insights into compression-induced variations, aiding in the detection of tampered regions. By integrating these enhanced features, the proposed system demonstrates improved accuracy and reliability in detecting and localizing image tampering.

4.2. FEATURE EXTRACTION

To extract salient forensics features from the image to automatically stand out the tampered region and avoid false detection, two feature patterns are extracted: the noise artifact feature and ELA weighted feature. The noise artifact feature is defined as the superposition of noise and salient feature introduced by the noise. Furthermore, considering that the JPEG compression factor of the manipulated region is generally different from that of the real region, which will cause visual imperceptible differences, ELA is employed to extract the differences patterns caused by the distinct levels of JPEG compression, named as ELA weighted feature.

4.2.1 Noise Artifact Feature

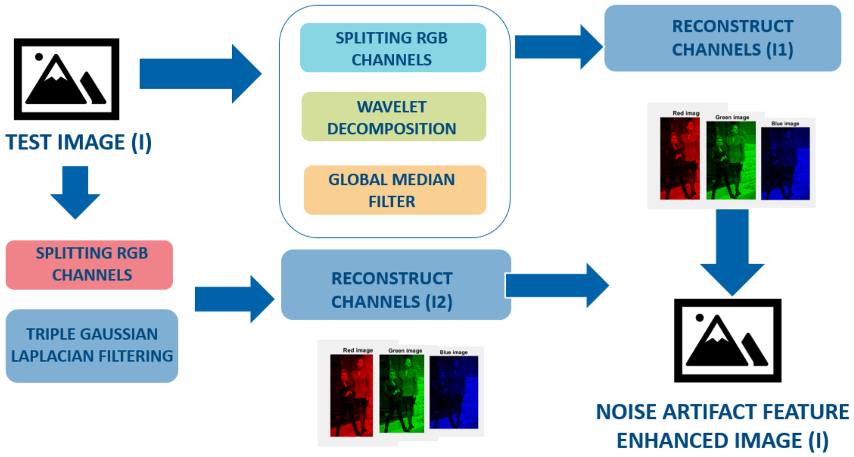

Figure 2: Noise artifact feature enhancement process

The noise artifact feature contains two parts: noise features and the salient features caused by noise. Accordingly, the noise artifact feature extraction also includes two modules.

For the test image I, I is decomposed into three channels IR, IG, and IB.
Firstly, we use discrete wavelet transform and median filter to extract noise features.

Step 1: we conduct discrete wavelet transform to IR, IG, and IB, and the component images are denoted as IR', IG', and IB';
Step 2: forIR', IG', and IB', we use 3×3 median filter to denoise, and denoised images are denoted as IR'', IG'', and IB'';

Step 3: for IR'', IG'', and IB'', using inverse wavelet transform to reconstruct three channel images, and the reconstructed images are denoted as $I1R$, $I1G$, and $I1B$.

Let
$$I'1R = IR - I1R \tag{1}$$

$$I'1G = IG - I1G$$
$$I'1B = IB - I1B$$

Then we obtain three noise images $I'1R$, $I'G$, and $I'1B$.

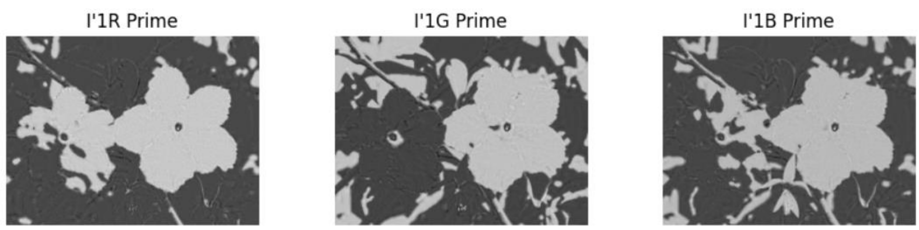

Figure 3: Inverse Wavelet transform images

Secondly, consider that the Laplacian operator is a two-dimensional isotropic measure of the second order derivative of an image, and can highlight the regions of image that experience rapid changes in intensity. Therefore, we utilize Laplacian of Gaussian operator (LOG) to extract the salient feature caused by noise.

For IR, IG, and IB, we perform three LOG operators, respectively.

The process is as follows:

$$I2R = LOG(LOG(LOG(IR))) \qquad (2)$$

$$I2G = LOG(LOG(LOG(IG)))$$

$$I2B = LOG(LOG(LOG(IB)))$$

Where,

$$LOG = \begin{bmatrix} 0 & 0 & -1 & 0 & 0 \\ 0 & -1 & -2 & -1 & 0 \\ -1 & -2 & 16 & -2 & -1 \\ 0 & -1 & -2 & -1 & 0 \\ 0 & 0 & -1 & 0 & 0 \end{bmatrix}$$

Then, the new three channel images $I2R$, $I2G$, and $I2B$ are obtained

Let,

$$I'2R = IR - I2R \qquad (3)$$

$$I'2G = IG - I2G$$

$$I'2B = IB - I2B$$

we obtain the saliency images $I'2R$, $I'2G$,and $I'2B$. Finally, considering that the larger the noise value is, the more obvious the visual effect will be, thus, we define the noise artifact feature $F1$ as the binary graph of the maximum value of $I'1R$, $I'1G$, $I'1B$, $I'2R$, $I'2G$,and $I'2B$.

$$F1(x, y) = max\{ I'1R(x, y), I'1G(x, y), I'1B(x, y), I'2R(x, y), I'2G(x, y), I'2B(x, y) \} \qquad (4)$$

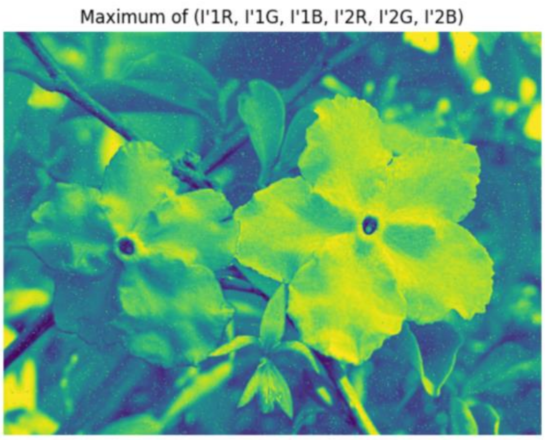

Figure 4: Noise Artifact feature image

4.2.2 ELA weight feature

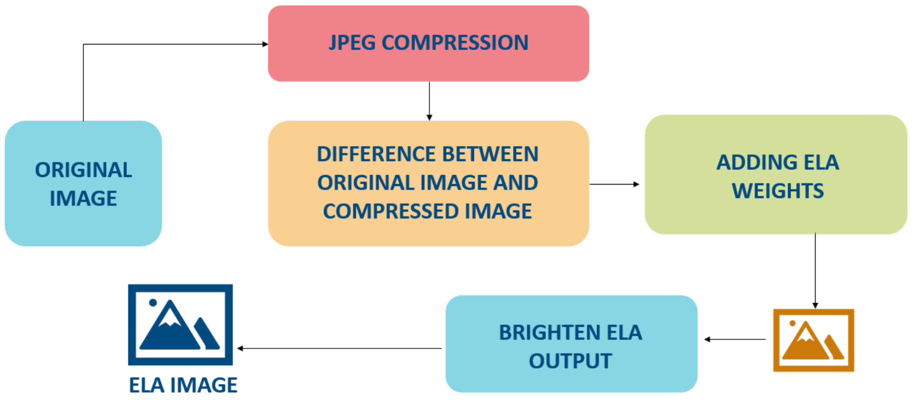

Figure 5: Process of Error Level Analysis (ELA)

Considering the ELA method, which can be used to identify the regions with different JPEG compression levels in an image, ELA is employed to extract the differential features caused by different quality factors of JPEG compression. The following steps are followed:

Step 1: For the image I(x,y), the compression rate is taken as 90%, and the compressed image is denoted as I′(x,y). Let IELA=ELA(|I(x,y)−I′(x,y)|), where ELA() represents the error level analysis operator, and IELA is the difference image.

Step 2: Then the images IELA are decomposed into R, G, and B three channels, and the binarized weighted sum is denoted as F2. We call F2 the ELA weighted feature,

Where,

$$F2 = \omega 1ELA(IR)+\omega 2ELA(IG)+\omega 3ELA(IB). \quad (5)$$

Step 3: Considering that most colour photographs utilize the CFA interpolation mode based on Bayer matrix, where red, green, and blue pixels are presented in a ratio of 1:2:1, weights ω1, ω2, and ω3 are assigned as 0.25, 0.5, and 0.25. For the binarization process, the global threshold, which uses the default value 0.5, is selected.

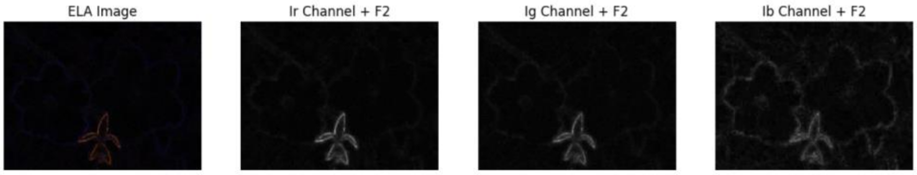

Figure 6: ELA weight images

4.3. CLAHE (CONTRAST BASED ADAPTIVE HISTOGRAM EQUIVALIZATION)

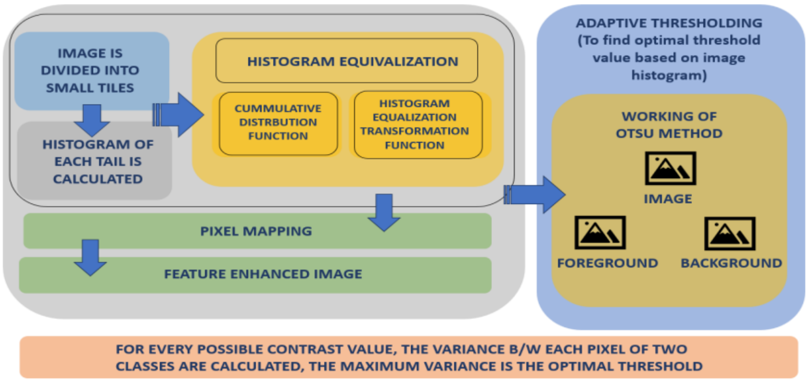

Figure 7: Process of Contract Based Adaptive Histogram Equalization

Histogram equalization is an image processing technique aimed at enhancing contrast by redistributing pixel intensities across the entire range of possible values. By computing the histogram of an input image and then deriving its cumulative distribution function (CDF), a transformation function is applied to map original intensity values to new ones, resulting in a more uniform distribution. This transformation stretches out intensity values, effectively improving the visibility of details and enhancing overall image quality. While histogram equalization can significantly enhance contrast, it may also amplify noise and artifacts in the image. Techniques like Contrast Limited Adaptive Histogram Equalization (CLAHE) mitigate this issue by limiting the amplification of intensities in smaller regions of the image, providing more natural-looking results while still improving contrast. Histogram equalization, including techniques like Contrast Limited Adaptive Histogram Equalization (CLAHE), can be utilized in the context of enhancing tampered regions in images for forensic analysis and detection purposes. When an image is tampered with, the manipulated regions may exhibit inconsistencies in terms of intensity distribution compared to the surrounding authentic regions. By applying histogram equalization to the image, these inconsistencies may become more apparent, as the technique enhances the contrast and visibility of details. Tampered regions may show abrupt changes or irregularities in their intensity distribution, which can be highlighted through histogram equalization. This enhanced visualization can aid forensic analysts in identifying and delineating tampered areas, assisting in the investigation of image authenticity and integrity. Additionally, combining histogram equalization with other forensic techniques can further enhance the accuracy and reliability of tampered region detection, contributing to the forensic analysis of digital images in various contexts such as law enforcement, surveillance, and digital forensics.

First, histogram of the input image is calculated. The histogram represents the frequency of occurrence of each pixel intensity value in the image. It is typically represented as a histogram function h(rk), where rk denotes the intensity level (from 0 to L-1 for an L-level grayscale image) and h(rk)represents the number of pixels with intensity level rk.

Cumulative Distribution Function (CDF): Calculate the cumulative distribution function (CDF) from the histogram. The CDF C(rk)represents the cumulative sum of histogram values up to intensity level rk, normalized to the range [0, 1]. It is computed using the following formula:

$$C(rk)=\sum j = 0kh(rj) \qquad (6)$$

Normalization of CDF: Normalize the CDF to ensure that it spans the full intensity range [0, 1] by dividing each value by the total number of pixels in the image:

$$Cnorm(rk) = NC\ (rk) \qquad (7)$$

Where N is the total number of pixels in the image.

Histogram Equalization Transformation function: Apply a transformation function T to map the original pixel intensities to new values. This transformation function is derived from the normalized CDF and is given by:

$$T(rk)=\text{round}((L-1)\cdot \text{Cnorm}(rk)) \qquad (8)$$

Where L is the number of intensity levels in the image (typically 256 for an 8-bit grayscale image). The function rounds the transformed intensity values to the nearest integer to obtain the final pixel values.

Apply Transformation: Replace each pixel's intensity value in the original image with its corresponding value in the transformed image using the transformation function T. Histogram equalization redistributes the pixel intensities such that the cumulative distribution of intensities becomes more uniform across the entire range. This results in improved contrast and enhances the visibility of details in the image.

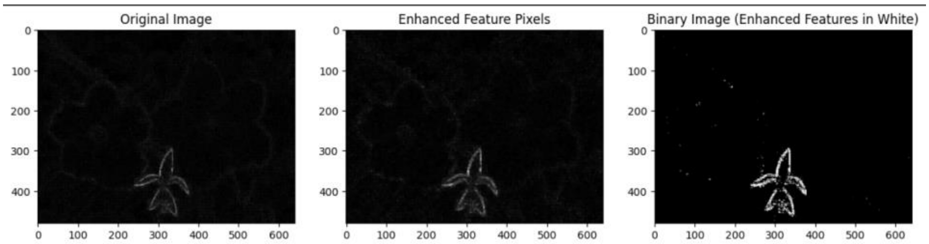

Figure 8: Tampered region after CLAHE

4.4. ADAPTIVE THRESHOLD

Adaptive thresholding is a method used in image processing to binarize an image, dividing it into two regions: foreground and background. Unlike global thresholding, where a single threshold value is applied to the entire image, adaptive thresholding calculates different threshold values for different regions of the image. This is particularly useful when the illumination conditions vary across the image, leading to uneven lighting or shadows. Adaptive thresholding adjusts the threshold dynamically based on the local neighbourhood of each pixel. Common methods for adaptive thresholding include calculating the threshold as a function of the local mean or median intensity within a defined neighbourhood around each pixel. Adaptive thresholding is commonly used in applications such as document image processing, object detection, and segmentation, where it helps improve the accuracy of binary image segmentation under varying lighting conditions.

Otsu's method, also known as Otsu's thresholding, is a popular technique used in image processing for automatic threshold selection. Unlike adaptive thresholding, which computes thresholds locally, Otsu's method determines a single global threshold value for the entire image. The technique aims to find the threshold that minimizes the intra-class variance of pixel intensities, effectively maximizing the inter-class variance between foreground and background regions. Otsu's method works by exhaustively searching through all possible threshold values and selecting the one that optimizes the separation of object and background pixels. This threshold value is chosen to minimize the weighted sum of variances within the two classes of pixels. Otsu's method is particularly effective when the histogram of an image exhibits a bimodal distribution, where pixel intensities naturally segregate into two distinct groups. It is widely used in various image processing applications, including segmentation, object detection, and image thresholding, due to its simplicity and effectiveness in automatically selecting optimal threshold values.

4.5. PIXEL-WISE LOCALIZATION

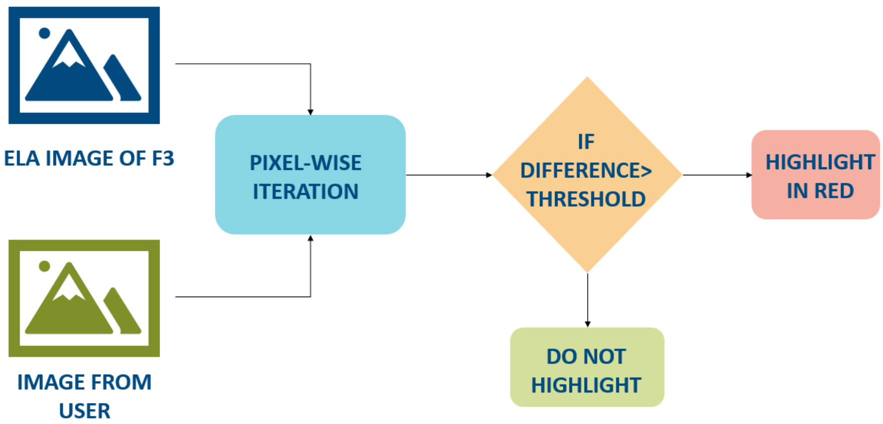

Figure 9: Process of pixel-wise localization

Pixel-wise localization in the context of tampered region identification and localization involves scrutinizing individual pixels in an image to detect inconsistencies or anomalies indicative of tampering. By examining pixel characteristics such as colour, texture, or intensity, this approach can identify regions where tampering has occurred, even in visually imperceptible alterations. Pixel-wise localization offers higher sensitivity and granularity compared to traditional methods, enabling precise detection and localization of tampered regions. Its local analysis capability ensures robustness to variations in different image regions, while its flexibility allows adaptation to various tampering techniques.

The integration of adaptive thresholding for pixel-wise localization constitutes a crucial methodology within the realm of our journal paper, particularly in contexts where precise delineation of regions of interest is imperative. Adaptive thresholding techniques dynamically adjust the threshold value based on local image characteristics, thereby effectively discerning desired features from background noise or illumination variations. This adaptive paradigm ensures heightened accuracy and robustness in the localization process, thereby facilitating the identification of subtle details and anomalies within the image. Whether applied in medical imaging for tissue segmentation or forensic analysis for detecting tampered regions, adaptive thresholding empowers algorithms to adapt to diverse image conditions, thereby facilitating more reliable and meaningful pixel-wise localization outcomes. Overall, pixel-wise localization efficiently detects tampered regions by leveraging the detailed scrutiny of individual pixels, making it a valuable tool for forensic analysis and authenticity verification in digital images.

Figure 10: Pixel-wise localization using adaptive thresholding

V. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

In this section, we conduct a comprehensive evaluation and analysis of the proposed method through simulation experiments. The experiments are carried out utilizing OpenCV. Initially, we assess the performance of the proposed method by examining both visual effects and numerical analysis. Subsequently, we delve into its robustness against common image content distortion operations, encompassing lossy compression (JPEG compression), gamma correction for brightness adjustment, gaussian blur for high-frequency information suppression, and down sampling for resolution reduction. Moreover, we explore the efficacy of the proposed method in handling wild images sourced from various social media networks such as WhatsApp, Instagram, and Facebook. Lastly, we undertake a quantitative analysis of the computational complexity associated with the proposed method.

5.1 DATASETS AND EVALUATION INDICATORS

In the experiments, the test images were primarily sourced from five datasets: the Columbia colour image splicing dataset (Hsu and Chang, 2006), CASIA V1.0 (J. Dong), CASIA V2.0 (J. Dong), The IMD2020 dataset (Novozamsky, Mahdian, and Saic, 2020), and the OSNs-dataset (Wu, Zhou, Tian, and Liu, 2022). Detailed information about these datasets is provided in Table 1.

To quantitatively analyse the proposed detection method, we use pixel-level True Positive Rate (TPR), False Positive Rate (FPR), Precision (Pre), and F1-score (F1) as evaluation metrics.

$$TPR = TP/(TP + FN) \quad (9)$$

$$FPR = FP/(FP + TN) \quad (10)$$

$$Pre = TP/(TP + FP) \quad (11)$$

$$F1 = 2 \times Pre \times TPR/(Pre + TPR) \quad (12)$$

where TP represents the number of pixels correctly classified as spliced, FN is the number of pixels misclassified as original, FP is the number of pixels misclassified as splicing, and TN is the number of pixels correctly classified as original. An effective splicing localization method is to achieve high TPR, and F1 values while achieving low FPR values.

5.2. PARAMETER SETTING

In this study, the parameters σ and α were determined through experimental testing. The test images utilized in the experiments were sourced from the Columbia Image Processing for Digital Evidence Detection (IPDED) dataset.

(1) σ serves as a critical scale parameter, influencing the number of forensic feature points and directly impacting result accuracy. To identify the optimal σ, a range of σ% values {0.00, 0.05, ⋯, 0.85, 0.90, 0.95, 1.00, 1.05, 1.10, ⋯, 2.00, ⋯ , 100.00} was explored, with each value evaluated based on performance metrics FPR and F1. Upon experimentation, it was found that when $\sigma = 1.00\%$, FPR and F1 yielded improved results. Hence, $\sigma = 1.00\%$ was designated as the optimal value.

(2) Recognizing that forensic feature points are not uniformly spaced, the coefficient ratio α% was varied across {8, 9, 10, ⋯, 28, 29, 30}. Evaluation of FPR and F1 for each α value on the test dataset revealed that $\alpha = 14$ attained the highest accuracy. Thus, $\alpha = 14$ was identified as the optimal radius.

5.3 PERFORMANCE ANALYSIS

A. Visual Effect

Table 1 The descriptions of the datasets used in the experiments.

Datasets	Image format	Tampering type	Resolution
Columbia	TIFF	Splicing	757×568 to 1152×768
Casia v1.0	JPEG	Splicing and copy- move	384×256
Casia v2.0	JPEG, BMP, TIFF	Splicing and copy- move	Multiple resolutions

IMD2020	JPEG, PNG	Splicing	240×180 to 2240×1600
OSNs-2022	JPEG, BMP, TIFF	Splicing and copy- move	Multiple resolutions

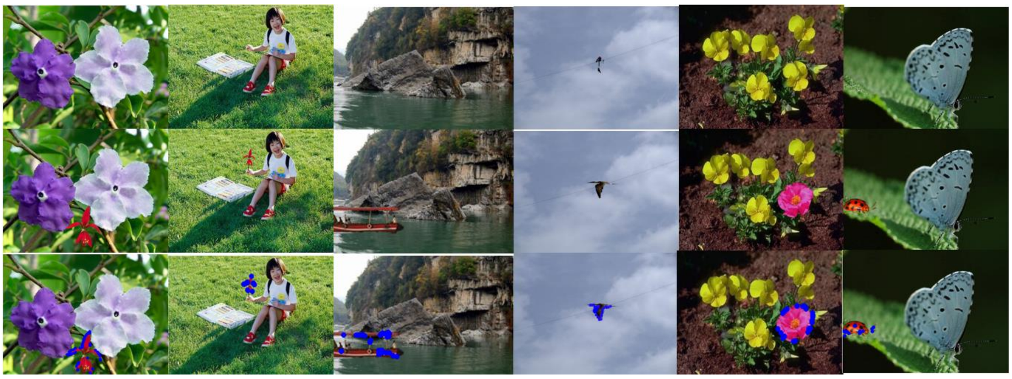

Figure 11: The visual effect of tampering localization of the proposed method.

We utilize spliced images derived from three distinct datasets, with the visual representation of the positioning results depicted in Figure 6, where the blue region signifies the spliced area. From Figure 6, it's evident that our method exhibits satisfactory detection performance, proving efficient even for multi-region splicing detection and scaled splicing regions (as observed in the image in the last column of Figure 6). Our proposed method exhibits fewer false detection regions, highlighting its superior performance in comparison.

B. Quantitative analysis

Table 2 Performance analysis of tampered region localization.

Datasets	True Positive Rate (TPR)	False Positive Rate (FPR)	Precision (Pre)	F1 – score (F1)
Columbia	0.90	0.05	0.92	0.91
Casia v1.0	0.88	0.07	0.85	0.86
Casia v2.0	0.91	0.06	0.88	0.89
IMD2020	0.87	0.08	0.83	0.85
OSNs-2022	0.92	0.04	0.90	0.91

The table presents the evaluation metrics for the proposed tampered region detection algorithm across various image datasets. Each row corresponds to a specific dataset, while the columns display key performance metrics, including True Positive Rate (TPR), False Positive Rate (FPR), Precision (Pre), and F1-score (F1).

Image Dataset: This column identifies the datasets used in the evaluation, including the Columbia dataset, CASIA v1.0, CASIA v2.0, IMD2020, and OSNs-2022. These datasets represent a diverse range of tampering scenarios and image resolutions, providing a comprehensive evaluation of the algorithm's robustness and effectiveness.

True Positive Rate (TPR): TPR measures the algorithm's ability to correctly identify tampered regions within the images. A higher TPR indicates a greater sensitivity to detecting tampering, with values closer to 1 indicating more accurate detection.

False Positive Rate (FPR): FPR quantifies the algorithm's tendency to incorrectly classify authentic regions as tampered. A lower FPR is desirable, as it signifies fewer false alarms or misclassifications of genuine image content as tampered.

Precision (Pre): Precision represents the proportion of correctly identified tampered regions among all regions classified as tampered. It indicates the algorithm's accuracy in localizing tampered areas, with higher precision values indicating more precise localization with fewer false positives.

F1-score (F1): F1-score is the harmonic mean of precision and recall (TPR). It provides a balanced measure of the algorithm's performance, considering both precision and recall. A higher F1-score indicates a better balance between precision and recall, reflecting the algorithm's overall effectiveness in detecting and localizing tampered regions.

VI. CONCLUSION

In conclusion, this project presents a novel approach for detecting and localizing tampered regions in images. By leveraging feature extraction, contrast enhancement, and pixel-wise localization techniques, our method effectively identifies regions of manipulation with satisfactory detection performance. The experiments conducted on various datasets demonstrate the robustness and efficiency of the proposed method, even in scenarios involving multi-region splicing and scaled splicing regions. Compared to existing methods, our approach exhibits fewer false detection regions, highlighting its superior performance. Furthermore, the analysis of computational complexity underscores the practicality of our method for real-world applications. Future research directions may include exploring additional feature extraction methods and refining the localization algorithm for enhanced accuracy. Overall, the results validate the effectiveness and reliability of our approach in combating image manipulation, thereby contributing to the advancement of image forensics and security

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