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An Enhancement of Harris Corner Detector Algorithm Applied in Signature Forgery Detection System

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Abstract. Signature verification is crucial for confirming the authenticity of identities in both administrative and financial transactions, where signature forgery can lead to significant security risks. The Harris Corner Detector Algorithm is a widely used method for feature extraction in image processing; its application spans various domains, such as detection of signature forgery. While effective in identifying key features, noise significantly affects performance, especially with impulse noise like salt-and-pepper noise commonly found in signature images. To solve this problem, this study enhances the Harris Corner Detector Algorithm by applying a median filter before gradient calculation. This method removes noise without sacrificing the integrity of key features important in signature forgery detection. The study evaluates the original and the enhanced algorithm using standard image quality metrics. Peak Signal-to-Noise Ratio (PSNR) surged from an average of 13.6 dB to 43.28 dB, the Structural Similarity Index (SSIM) improved significantly from 78% to 94%, and the Mean Squared Error (MSE) dropped substantially from 16.74 to 3.84. These advancements resulted in a more reliable algorithm, exhibiting excellent resistance to noise while maintaining image structure, making the enhanced algorithm highly effective for accurate signature forgery detection.

Keywords Harris Corner Detector Algorithm, Signature Forgery Detection, Feature Extraction, Image Processing, Median Filter

1. INTRODUCTION

As signatures serve as one of the primary means of identification, verifying signatures has become critical in safeguarding identities during administrative and financial transactions. The 2023 LPL Financial case of falsified e-signatures resulted in a $3 million fine (Brasseur, K., 2023). In 2024, the American Bankers Association reported that losses from check fraud are expected to reach $24 billion (McGortey, L., 2024). Numerous other cases involving forged signatures in contracts, deeds, prescriptions, court documents, certificates, wills, and land titles highlight the widespread impact of signature fraud across various sectors. These challenges highlight the importance of a reliable signature verification system to protect critical transactions more than ever.

This study focuses on enhancing the Harris Corner Detector Algorithm, a widely recognized method for feature extraction in image processing. The algorithm works by computing the local autocorrelation matrix for each pixel in the image, identifying regions where the intensity varies significantly in multiple directions, which correspond to corner points (Han et al., 2019). The original algorithm effectively identifies key features within

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an image; however, its performance can be severely compromised by impulse noise, frequently encountered in scanned signature images (Luo, C. et al., 2021). To address this challenge, a median filter is integrated prior to the gradient calculation. This novel approach aims to mitigate noise while preserving the integrity of features, improving the algorithm's reliability in real-world applications, particularly in the detection of signature forgery.

To assess the performance of both the original and enhanced versions of the algorithm, standard image quality metrics were used, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE). These metrics provide a comprehensive analysis of the improvements in noise resistance, structural integrity, and detection accuracy (Sara et al., 2019). The datasets used in this study were sourced from the Kaggle "Signature Verification Dataset" by Robin Reni, which are extracted from the ICDAR 2011 Signature Dataset, the CEDAR-Dataset, and the Offline Handwritten Signature Database based on Age Annotation (OHSDA) by Sathish Kumar and Dr. Shivanand Gornale. These diverse datasets provided a solid foundation for evaluating the effectiveness of the enhanced algorithm in addressing signature forgery detection challenges.

The integration of the median filter before gradient calculation not only improved the algorithm's resilience to noise but also demonstrated its adaptability across diverse datasets with varying noise levels, highlighting the importance of enhancing fundamental algorithms to meet the demands of real-world applications. By optimizing the algorithm for signature verification systems, this study contributes to the field of image processing and security, providing a robust method that strengthens the accuracy and reliability of identity confirmation processes, thereby fostering greater trust and confidence in signature-based authentication systems.

2. LITERATURE REVIEW

A. Signature Forgery

A signature is a unique handwritten mark that a person uses to identify themselves. It is commonly used on checks, legal documents, contracts, and other papers. Each person's signature is a specific pattern of pixels that is unique to them (Poddar et al., 2020). As trade and commerce have grown, so has the reliance on signatures. This increased reliance has made it crucial for organizations to protect customer information and verify the authenticity of stored data. Ensuring the legitimacy of signatures has become essential in today's world (Ashraf, 2023).

Signature forgery, a deliberate act of deception, is a global crime with serious financial and identity-related consequences. This includes fraudulent activities like selling forged celebrity signatures or counterfeiting and cashing checks. Manual signature verification by experts is a costly and time-consuming process, adding significant financial burdens to individuals and businesses (Bird et al., 2023).

A signature forgery detection system analyzes a test signature to determine if it is genuine or forged. If the test signature matches the person's known signature, it is considered authentic. However, if it's an imitation or random mark that doesn't match the person's signature, it's classified as a forgery (Longjam et al., 2023). Offline handwriting identification involves writing on paper with traditional tools, which is then captured as an image. Features extracted from these images can be combined to create unique and effective characteristics. Offline signature verification is practical because of its popularity and the clear structural information it provides, which reflects the writer's characteristics (Lu et al., 2022).

B. Harris Corner Detector Algorithm

The Harris Corner Detector Algorithm, introduced by Harris and Stephens in 1988, drew inspiration from the research conducted by Moravec. The Harris corner detector is a commonly used method for identifying points of interest within an image. Its effectiveness stems from its simplicity and computational efficiency. By utilizing information from the autocorrelation matrix and analyzing its eigenvalues, the Harris detector is able to identify areas within a local neighborhood where there are significant changes in intensity. This matrix, also known as the structure tensor, serves as a fundamental component for addressing various image processing tasks, including the estimation of optical flow between two images (Sánchez et al., 2019).

Corners represent vital local features within an image, typically occurring where there is a sharp change in brightness or where image contour boundaries intersect. These corner points are extensively utilized in computer vision tasks such as 3D scene reconstruction, motion estimation, object recognition, and image registration (Luo, C. et al., 2021). Corner detection is valuable in image processing because it preserves directional information. This information is crucial for tasks like image matching, where it provides a stable reference point. The Harris corner detector, for instance, leverages this information to accurately align images and match features, even in the presence of scene transformations or perspective changes (Karim & Sameer, 2019).

The Harris corner detection method, used in signature verification, identifies unique points within a signature image. It works by pinpointing image patches that significantly differ from their neighboring areas. A corner is identified as the intersection of edges. The algorithm detects these points by analyzing changes in image intensity. A significant change in intensity across different directions indicates the presence of a corner. (Priya et al., 2019). Although the Harris corner detection algorithm is widely used in many computer vision tasks, it has certain limitations. The Harris Corner Detector's sensitivity to noise, particularly impulse noise like salt-and-pepper noise, can lead to inaccurate detections. This is due to its reliance on local intensity gradients, which can be easily distorted by noise (Luo, T. et al., 2020).

C. Median Filter

Digital images are prone to noise, which is any unwanted information that degrades image quality. Noise, often seen as graininess in an image, refers to random variations in pixel intensity. It originates from fundamental physical factors like the particle nature of light or the thermal energy within image sensors. Noise can be introduced during image acquisition or transmission, leading to pixels showing inaccurate intensity values instead of their actual ones (Win et al., 2019). Impulse noise, a type of brief disturbance, can degrade image quality due to factors like atmospheric interference, temperature variations during image capture, or transmission channel issues. Unlike Gaussian noise, which affects pixels in a correlated manner, impulse noise randomly impacts specific pixels. Consequently, some pixels may be damaged while others remain unaffected. Removing noise is essential for successful image processing, as it preserves image details and improves the quality of subsequent processing steps. By reducing noise, the accuracy and efficiency of further image processing are enhanced (Sreejith & Nayak, 2020).

The Median Filter is a common technique for reducing noise, particularly effective against impulse noise like salt and pepper noise. It works by replacing each pixel's intensity with the middle value of its neighboring pixels, preserving edges while eliminating outliers. It's a popular choice for image restoration as it effectively reduces noise while preserving image details. Unlike linear smoothing filters that can blur images, median filters significantly minimize blurring, making them ideal for preserving high-frequency details (Draz et al., 2023). Tania and Rowaida's 2019 study compared the effectiveness of various filters (Mean, Median, Winner, Wavelet Transform (WT), and Curvelet Transform (CT)) in removing noise from aerial images. They evaluated the performance of these techniques using Mean Square Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). Their findings revealed that all filters and transforms performed similarly well in reducing Gaussian noise. However, for salt-and-pepper noise, filters, especially the median filter, outperformed transforms in terms of noise reduction.

3. METHODS

The Harris Corner Detector Algorithm is enhanced with a novel approach of utilizing median filtering during image preprocessing. This adjustment is designed to reduce impulse noise while preserving the structural integrity of the image, crucial for reliable key feature extraction in signature forgery detection.

A. Median Filter Algorithm

The median filter is implemented as a robust noise reduction technique that preserves edge and corner structures while attenuating noise (Draz et al., 2023). This technique replaces each pixel's intensity value with the median value within a W × W neighborhood, effectively suppressing noise while preserving edge structures (Hou et al., 2021). Algorithm 1 describes the median filtering process:

```
Algorithm 1: Median Filter

Input: Original image I, window size W
Output: Noise-reduced image I'
Allocate I'[width(I)][height(I)]  // Initialize output image
Allocate window[width(W) × height(W)]  // Allocate window array
edgex ← ⌊width(W) / 2⌋  // Calculate x-axis edge offset
edgey ← ⌊height(W) / 2⌋  // Calculate y-axis edge offset
for x ← edgex to width(I) - edgex do
    for y ← edgey to height(I) - edgey do
        window ← empty array
        i ← 0
        for fx ← 0 to width(W) do
            for fy ← 0 to height(W) do
                window[i] ← I[x + fx - edgex][y + fy - edgey]
                i ← i + 1
        Sort(window)
        I'[x][y] ← window[⌊width(W) * height(W) / 2⌋]
```

The median filter (Algorithm 1) operates by:

1. Defining a sliding window of size W × W
2. Collecting pixel values within the window
3. Sorting the collected values
4. Replacing the center pixel with the median value
5. Repeating steps 2-4 for all pixels in the image.

B. Enhanced Harris Corner Detector Algorithm

The Harris corner detection algorithm incorporates three user-defined parameters (Table 1) that modulate its performance:

Parameter	Description
k	Empirical sensitivity constant
Window Size	Local gradient computation area
Threshold	Harris response cutoff value

Table 1: Harris Corner Detector Algorithm Parameters

With these parameters established, we can now transition to the detailed steps of the Enhanced Harris Corner Detection Algorithm (Algorithm 2), which systematically integrates a median filter to enhance noise resilience for accurate detection.

Algorithm 2: Enhanced Harris Corner Detector

```
Input:
    I: Original signature image
    k: Sensitivity constant
    W: Window size
    T: Response threshold

Output:
    C: Set of detected corner points
    I': Preprocessed signature image

1:  Allocate I'[width(I)][height(I)]  // Initialize preprocessed image
2:  Allocate Ix[width(I)][height(I)]  // Gradient in x-direction
3:  Allocate Iy[width(I)][height(I)]  // Gradient in y-direction
4:  Allocate Ix²[width(I)][height(I)]  // Squared x-gradient
5:  Allocate Iy²[width(I)][height(I)]  // Squared y-gradient
6:  Allocate IxIy[width(I)][height(I)]  // Gradient product

// Preprocessing Stage
```

```
Convert I' to grayscale
I' ← MedianFilter(I, W)  // Noise reduction

// Gradient Computation
for x ← 1 to width(I') do
    for y ← 1 to height(I') do
        Ix[x][y] ← ∂I'[x][y]/∂x  // x-direction gradient
        Iy[x][y] ← ∂I'[x][y]/∂y  // y-direction gradient
        Ix²[x][y] ← Ix[x][y]²
        Iy²[x][y] ← Iy[x][y]²
        IxIy[x][y] ← Ix[x][y] * Iy[x][y]

// Derivative Smoothing
Ix² ← GaussianFilter(Ix², (W,W))
Iy² ← GaussianFilter(Iy², (W,W))
IxIy ← GaussianFilter(IxIy, (W,W))

// Harris Matrix Computation
Allocate R[width(I')][height(I')]  // Response matrix
for x ← W/2 to width(I') - W/2 do
    for y ← W/2 to height(I') - W/2 do
        Σ(Ix²) ← Sum of Ix² in W×W neighborhood
        Σ(Iy²) ← Sum of Iy² in W×W neighborhood
        Σ(IxIy) ← Sum of IxIy in W×W neighborhood

// Corner Response Calculation
    Det(M) ← Σ(Ix²) * Σ(Iy²) - [Σ(IxIy)]²
    Trace(M) ← Σ(Ix²) + Σ(Iy²)
    R[x][y] ← Det(M) - k * [Trace(M)]²

// Corner Point Identification
C ← ∅  // Initialize empty set of corner points
for x ← 1 to width(I') do
    for y ← 1 to height(I') do
        if R[x][y] > T and IsLocalMaximum(R, x, y) then
            C ← C ∪ {(x,y)}

return C, I'
```

The enhanced Harris Corner Detector (Algorithm 2) operates through six stages:

1. Image Preprocessing
    - Read the image and convert it to grayscale.
    - Apply median filtering to reduce noise
2. Gradient Computation
    - Calculate x-axis (Ix) and y-axis (Iy) gradients

- Compute products of derivatives: Ix^2, Iy^2, $Ix*Iy$

3. Derivative Smoothing
   - Apply gaussian filtering to smooth the products of derivatives
4. Harris Matrix Computation
   - Calculate the Harris Matrix (M) for each pixel:

$$M = \begin{bmatrix} \text{sum}(Ix^2) & \text{sum}(Ix*Iy) \\ \text{sum}(Ix*Iy) & \text{sum}(Iy^2) \end{bmatrix}$$

5. Corner Response Calculation
   - Compute the Harris Response (R) for each pixel using the determinant and trace of M:

$$R = \text{Det}(M) - k * (\text{Trace}(M)^2)$$

   - Where:

$$\text{Det}(M) = \text{sum}(Ix^2)*\text{sum}(Iy^2) - \text{sum}(Ix*Iy)^2$$

$$\text{Trace}(M) = \text{sum}(Ix^2) + \text{sum}(Iy^2)$$

k is an empirical constant, equal to 0.04

6. Corner Point Identification
   - Compare the Harris Response (R) to threshold (if R > threshold) to determine corner points.
   - Mark detected corner points in the output image.

In the proposed enhanced Harris Corner Detector algorithm, the median filter is integrated during the preprocessing stage, line 8 of Algorithm 2, to mitigate image noise and enhance feature detection reliability. By preprocessing the grayscale signature image with the median filter, the algorithm prepares the image for more robust gradient computation and subsequent corner response calculations.

C. Signature Forgery Detection System

The Signature Forgery Detection System was consists of three main phases:

1. Signature Detection:
   - YOLOv5 is employed to detect and crop signatures from documents efficiently.
2. Signature Cleaning:
   - Detected signatures undergo cleaning via CycleGAN, which removes stamps or printed text that may interfere with accurate verification.

3. Signature Verification:

- The enhanced Harris Corner detection algorithm is applied to preprocessed images to extract corner features. These features are then integrated into a VGG16-based feature extraction process.
- The final step involves computing cosine similarity between the cleaned signature and a reference signature to determine their match

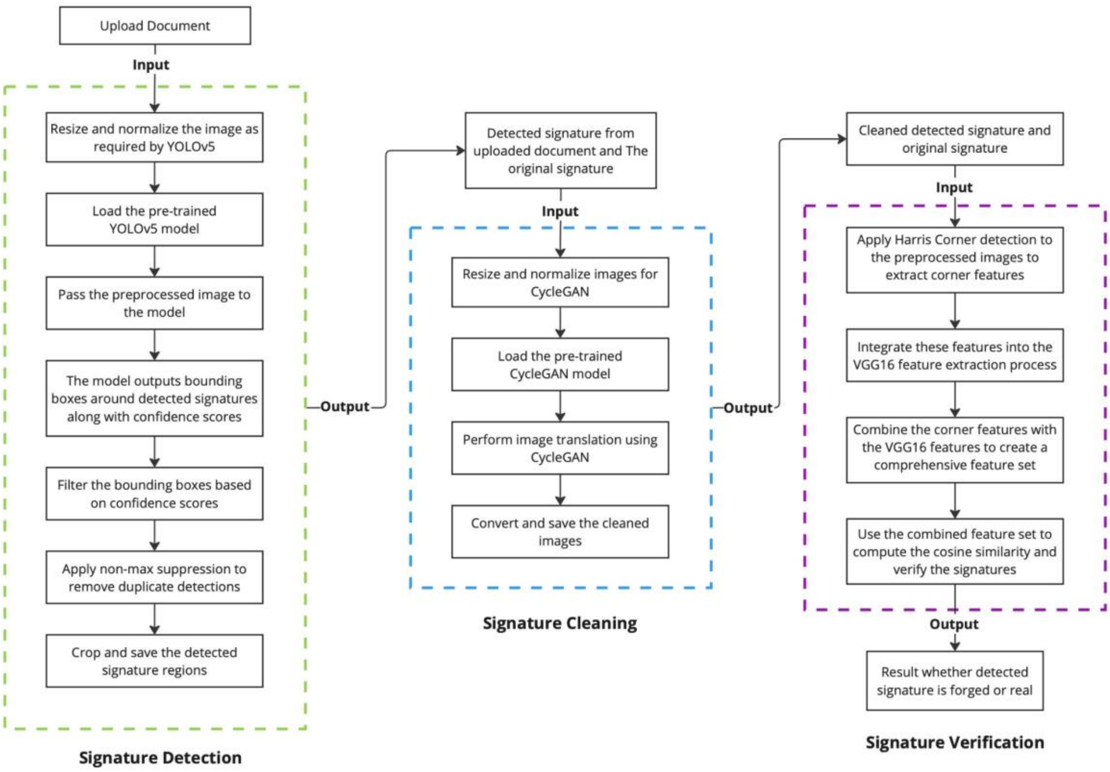

Figure 1: Signature Forgery Detection System Architecture

Figure 1 illustrates the comprehensive workflow of the used signature forgery detection system, which integrates state-of-the-art deep learning and computer vision methodologies. Leveraging YOLOv5 for precise signature localization, CycleGAN for signature cleaning, and enhanced Harris Corner Detector Algorithm with VGG16 neural architecture for signature verification, offering a comprehensive approach to signature verification.

D. Signature Dataset Composition

The algorithmic evaluation employed a comprehensive multi-source signature dataset, strategically selected to encompass diverse morphological and demographic variations (Table 2):

Dataset	Source	Characteristics
Signature Verification Dataset (ICDAR 2011 Signature Dataset)	From Kaggle by Robin Reni extracted from ICDAR 2011 Signature Dataset	Contains a total of 771 images of genuine and forged signatures from Dutch writers
CEDAR-Dataset	From Kaggle by Shreelakshmi G. Prakash	Contains a total of 2640 images of genuine and forged signatures
Offline Handwritten Signature Database based on Age Annotation (OHSDA)	From Mendeley Data by Sathish Kumar and Dr Shivanand Gornale	Contains a total of 6010 images of genuine and forged signatures

Table 2: Signature Dataset Composition

These datasets shown in Table 2 provided a wide range of signature samples, facilitating comprehensive testing of the performance of the enhanced algorithm.

E. Performance Evaluation Metrics

To assess the performance of both the original and enhanced algorithms, standard image quality metrics were employed:

- **Mean Square Error (MSE)** – This metric measures the cumulative error between the original and processed images. A lower MSE value signifies better image quality, as it indicates less deviation from the original image (Al Najjar, 2024). To calculate MSE:

$$\mathrm{MSE} = \frac{1}{m \times n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2$$

Where *m* and *n* are the dimensions of the images (height and width). *I(i, j)* and *K(i, j)* are the pixel values of the original image and the processed image, respectively.

- **Peak Signal-to-Noise Ratio (PSNR)** – This metric evaluates the ratio of signal power to noise power. Higher PSNR values indicate improved noise resistance, as the signal remains strong relative to noise (Sara et al., 2019). To calculate PSNR:

$$\mathrm{PSNR} = 10 \times \log_{10}\left(\frac{\mathrm{MAX}^2}{\mathrm{MSE}}\right)$$

Where MAX is the maximum possible pixel value of the image, while MSE denotes the calculated Mean Square Error.

- **Structural Similarity Index (SSIM)** – SSIM assesses the image quality by comparing luminance, contrast, and structural information between images. The score ranges from 0 to 1, with a value closer to 1 indicating greater similarity and minimal degradation (Al Najjar, 2024). To calculate SSIM:

Step 1: Split the original image and the processed image into smaller overlapping windows.

Step 2: Calculate Luminance Component *(l(x,y))*

I. Compute Mean Intensities

a. Calculate the mean intensity *(μx)* for the window from image *I*.

b. Calculate the mean intensity *(μy)* for the corresponding window from image *K*.

$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i \quad \text{and} \quad \mu_y = \frac{1}{N}\sum_{i=1}^{N} y_i$$

Where *N* is the total number of pixels in the window.

II. Compute the Luminance Formula

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}$$

Where *C1* is a small constant to prevent division by zero, often defined as *C1=(K1L)2* where *K1* is a small constant and *L* is the dynamic range of pixel values.

Step 3: Calculate Contrast Component *(c(x,y))*

I. Compute Standard Deviations

a. Calculate the standard deviation *(σx)* for the window from image *I*.

b. Calculate the standard deviation *(σy)* for the window from image *K*.

$$\sigma_x = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)^2} \quad \text{and} \quad \sigma_y = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(y_i - \mu_y)^2}$$

II. Compute the Contrast Formula

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}$$

Where *C2* is a small constant to avoid division by zero, often defined as *C2=(K2L)2* where *K2* is typically 0.03.

Step 4: Calculate the Structure Component *(s(x,y))*

I. Compute the Covariance

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)(y_i - \mu_y)$$

II. Compute the Structure Formula

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x \sigma_y + C_3}$$

Where *C3* is often defined as *C3=C2/2* to maintain consistency.

Step 5: Combine the Components to Compute SSIM for Each Window

$$\mathrm{SSIM}(x,y) = [l(x,y)]^{\alpha} \cdot [c(x,y)]^{\beta} \cdot [s(x,y)]^{\gamma}$$

Where, α,β,γ are set to 1 for simplicity

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

Step 6: Average the SSIM Values Across the Image

$$\text{Overall SSIM} = \frac{1}{M}\sum_{j=1}^{M}\mathrm{SSIM}(x_j, y_j)$$

Where *M* is the total number of windows

To assess the improved Harris Corner Detector, we used three metrics (MSE, PSNR, SSIM) on three datasets (ICDAR 2011 Signature, CEDAR, OHSDA). To avoid the impact of extreme values and skewed data, the median values for each dataset were used, providing a more reliable representation of central tendency. Finally, the overall performance of both the original and enhanced algorithms was determined by averaging the median values across all datasets.

4. RESULTS

The performance of the original and enhanced Harris Corner Detector algorithms was evaluated using three standard image quality metrics: Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). The experimental environment consisted of Python 3.12.2 running on an Apple MacBook Air (M1, 8-core CPU, 8GB RAM) with macOS Sonoma 14.0. The parameters used were: k=0.04

(sensitivity constant), window size = 3 (context preservation), and threshold = 10,000 (cutoff value).

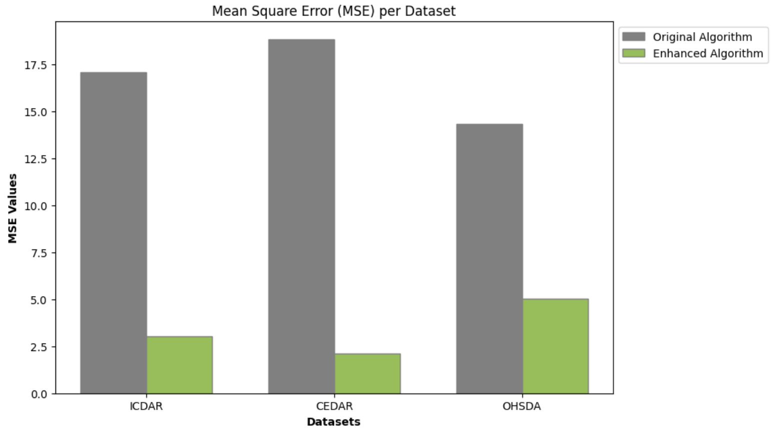

Figure 1: Main Square Error(MSE) per Dataset

Figure 1 illustrates a substantial reduction in the Mean Square Error (MSE) metric achieved by the enhanced Harris Corner Detector Algorithm compared to the original implementation. Across the three test datasets, the original algorithm exhibited an MSE of 17.0949, 18.8277, and 14.3090. In contrast, the enhanced algorithm achieved a significantly lower overall MSE of 3.0309, 2.0989, and 5.0283 for the ICDAR, CEDAR, and OHSDA.

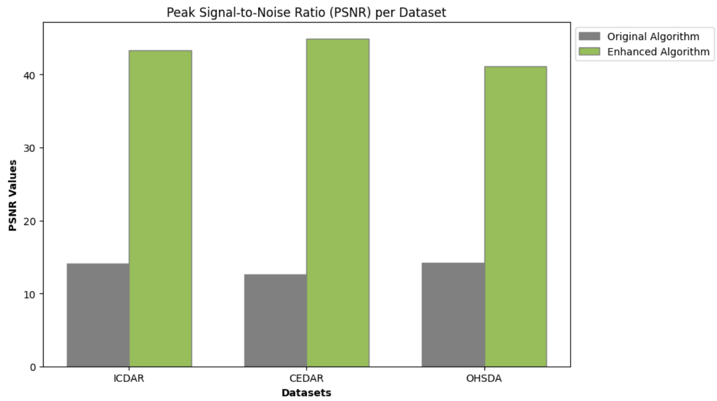

Figure 2: Peak Signal-to-Noise Ratio (PSNR) per Dataset

Figure 2 shows an increase in Peak Signal-to-Noise Ratio (PSNR) achieved by the enhanced Harris Corner Detector algorithm compared to the original implementation. The original implementation obtained PSNR values of 14.0898 dB (ICDAR), 12.5862 dB (CEDAR) and 14.1622 dB (OHSDA). Conversely, the enhanced algorithm demonstrated a remarkable improvement, achieving PSNR values of 43.3149 dB (ICDAR), 44.9107 dB (CEDAR) and 41.1165 dB (OHSDA).

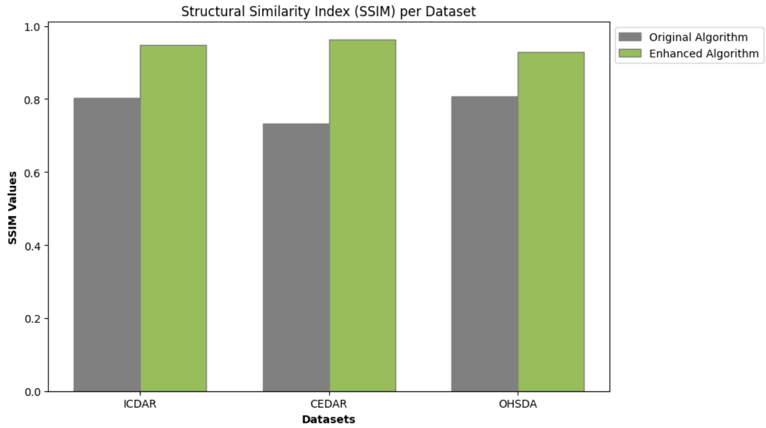

Figure 3: Structure Similarity Index (SSIM) per Dataset

Figure 3 presents a significantly higher Structure Similarity Index (SSIM) achieved by the enhanced Harris Corner Detector algorithm compared to the original implementation. The original algorithm achieved SSIM values of 0.8034 (ICDAR), 0.7323 (CEDAR), 0.8069 (OHSDA). In contrast, the enhanced algorithm attained greater SSIM values of 0.9488 (ICDAR), 0.9630 (CEDAR), 0.9285 (OHSDA).

The results are summarized in the following tables, which present the metrics for each dataset as well as overall averages:

	MSE	PSNR	SSIM
ICDAR 2011 Signature Dataset	17.0949	14.0898 dB	0.8034
CEDAR-Dataset	18.8277	12.5862 dB	0.7323
OHSDA	14.3090	14.1622 dB	0.8069
OVERALL	**16.7439**	**13.6127 dB**	**0.7809**

Table 1: Original Harris Corner Detector Algorithm Results

	MSE	PSNR	SSIM
ICDAR 2011 Signature Dataset	3.0309	43.3149 dB	0.9488
CEDAR-Dataset	2.0989	44.9107 dB	0.9630
OHSDA	5.0283	41.1165 dB	0.9285
OVERALL	**3.3861**	**43.1140 dB**	**0.9468**

Table 2: Enhanced Harris Corner Detector Algorithm Results

The improved algorithm outperforms the original in terms of Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). The MSE decreased by 79.8%, from 16.7439 to 3.3861, indicating significantly less error. The

PSNR increased by 29.5 dB, from 13.6127 dB to 43.1140 dB, suggesting much better reconstruction quality. The SSIM also improved by 21.3%, from 0.7809 to 0.9468, demonstrating better preservation of structural details. Overall, the enhanced algorithm shows superior performance across all three datasets in terms of MSE, PSNR, and SSIM.

5. DISCUSSION

This study aimed to enhance the Harris Corner Detector Algorithm by addressing its intrinsic noise sensitivity through novel median filtering preprocessing. The primary contribution lies in systematically mitigating noise-induced degradation in feature extraction performance, thereby improving algorithmic reliability and precision. The experimental results demonstrate significant algorithmic improvements. The Peak Signal-to-Noise Ratio (PSNR) increased from 13.6 dB to 43.28 dB, indicating robust noise suppression. Correspondingly, the Structural Similarity Index (SSIM) rose from 78% to 94%, validating enhanced structural preservation. The Mean Squared Error (MSE) reduction from 16.74 to 3.84 further substantiates the preprocessing method's effectiveness.

Existing literature has consistently highlighted noise interference challenges in corner detection algorithms. Our proposed median filter integration represents a novel approach, surpassing traditional noise reduction techniques that often compromise critical image details. The enhanced algorithm exhibits substantial applicability in high-stakes domains such as forensic document analysis, digital signature verification, and other image processing tasks. However, limitations such as sample size and environmental variability may influence the study's validity. Future research could explore the algorithm's performance under diverse conditions, including varying lighting and complex

6. CONCLUSION

This research improved the Harris Corner Detector to make it less sensitive to noise, a crucial issue in applications like signature forgery detection. By adding a Median Filter before calculating gradients, the algorithm became more resilient to different types of noise, like salt-and-pepper and Gaussian noise. This improvement reduced false detections and preserved important image details, as shown by better PSNR, SSIM, and MSE scores. These results suggest that the improved algorithm is well-suited for high-precision applications, especially in offline signature verification systems. The integration of this filtering technique not only improved the algorithm's noise resilience but also showcased its adaptability across diverse datasets with varying noise levels. This improvement highlights the value of enhancing basic algorithms to meet the needs of real-world use, leading to more reliable and efficient systems for image processing and security.

7. LIMITATION

This study aimed to improve the Harris Corner Detector's noise resilience by using a Median Filter before gradient calculation. However, the evaluation was limited to controlled testing environments with pre-selected datasets and predefined noise conditions. This approach may not fully capture the complexities of real-world scenarios, such as dynamic lighting, varying noise patterns, and environmental disturbances. Therefore, the findings might not consistently apply to real-world situations. Additionally, the research focused on using the enhanced algorithm for static images in offline signature verification. It did not explore its use in video or real-time processing, limiting its applicability in dynamic environments like surveillance systems or motion tracking.

These limitations emphasize the need for future research to validate the algorithm's performance in various real-world conditions, optimize its efficiency for systems with limited resources, and explore its potential for real-time applications. While these limitations exist, the study still makes significant contributions to improving the Harris Corner Detector's noise resilience, especially for signature forgery detection.

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