

A Hybrid De-noising Approach Using the WGEAD Model with Edge Preservation

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Abstract—Image de-noising is a very crucial step in computer vision application, aims to eliminate unwanted noise from images without harming the texture and edges present. This paper proposes a Wavelet Guided Edge Aware De-Nosing Algorithm (WGEAD) Model for elimination of noise from the image and preserves the edges. The proposed WGEAD model uses a combination of Discrete Wavelet transform and selective Bilateral filtering for effective noise suppression. The proposed WGEAD initially uses soft thresholding for lowering noise and followed, by selective bilateral filtering to smooth the homogenous areas of the image without affecting the edges. The proposed WGEAD Model gives PSNR- 40.30 and SSIM-0.988 compared to the traditional methods, the WGEAD demonstrates effective noise removal with edge preservation.

Keywords—Image De-noising, SSIM, PSNR, DWT, Bilateral Filtering.

I. INTRODUCTION

In the field of Computer Vision, digital image processing plays an important role [13] in improvising the quality of the image and recovering the important information lost due to noise. Noise is unwanted which can be added to an image through compression, transmission, rain, environmental reasons, poor lighting etc.

The main aim of the de-noising techniques is to reduce the noise from the image without hampering the texture, edges, and fine details present in that image.

The traditional techniques like Gaussian filter, mean filter, median filter are quick and simple but sometimes makes image blur and causes loss of texture. The new techniques like DWT uses frequency information to separate the noise and component details while selective bilateral filtering smooths the image and preserves edges and texture.

The main contribution of this paper is developing a two stage WGEAD model that first reduces noise using DWT and smoothest the image using Selective Bilateral filtering. The selective filtering helps to reduce compilation time while maintaining the quality of image. The paper also compares the proposed model approach with existing methods using PSNR, SSIM and computation time.

The remainder of the paper is organised as follows: Section 2 presents comprehensive literature review on image de-noising methods. Section 3 describes the proposed WGEAD model approach using DWT and Selective Bilateral Filtering as backbone. Section 4 discusses about the experiment setup and presents the obtained results. Section 5 concludes the paper with outlining future work direction.

II. LITERATURE REVIEW

This literature review is conducted to study the advancements happened in noise reduction field in past decades. The prior researches have used classical and deep learning techniques for de-noising images. The review shown in Table 1 below outlines methodologies employed, summary and gaps noticed in their research. The main driving force behind the suggested methodology is the review's compiled conclusions.

Table 1. Comparison of Existing Techniques related to De-noising

Reference	Method	Summary	Weakness
Bo Chena et al.[1]	Modified BM3D	Developed a edge aware BM3D algorithm with adaptive thresholding	High computation cost, complex parameters
Wei Liang et al.[2]	Bilateral Hybrid Filtering(Guided and Median Filtering)	This approach develops Sharpe and noise free defogging images	The hybrid parameters are selected manually which limits are real time use of the approach.
Yuhang Geng et al. [3]	Proposed DBSnet using	It uses dual branch noise to noise based	Dual Branch make it slow, computationally

	DnCNN as backbone	approach for noise reduction.	lly expensive, require training
Y Song et al.[4]	Blind de-noising by using techniques of residual and attention mechanisms.	This approach dynamically skips residual blocks to make it computationally feasible.	Only works on global information and does not use local regions information and pixels.
Y Bai et al.[5]	Uses MSPNet which is multi-stage progressive de-noising network	De-noises the image in 3 stages .	High computation cost, can add artifacts in textural region
Alessandro et al. [6]	CPnP method reduces parameter tuning and works on image quality as compared to standard PnP.	Use learning based de-noising as constraints. Plug and play + ADMM	Computationally expensive and needs correct noise level estimation.

Most of the approaches studied needs prior assumptions or the approaches are computationally expensive and have limited real time use. The suggested method improves noise suppression while maintaining edge structures more successfully than traditional hybrid approaches by introducing selective bilateral filtering after DWT-based de-noising.

III. PROPOSED WORK

The suggested architecture combines multi-stage processing, including wavelet-based de-noising, flat-region recognition, and selective bilateral filtering, to efficiently reduce noise while maintaining structural information. The noisy input image is initially divided into approximation and detail coefficients, which represent low-frequency and peak frequency components, respectively, using the Discrete Wavelet Transform (DWT). Since noise is mostly concentrated in high-frequency components, the detail coefficients are subjected to soft thresholding in order to reduce noise while maintaining crucial signal properties.

Inverse wavelet transformation is then used to recreate the de-noised image. Local variance analysis is used to identify flat areas in the image following wavelet reconstruction. By identifying flat areas, the algorithm may apply smoothing just where it is required, avoiding over-smoothing of edges and places with a lot of texture. In order to minimize noise while maintaining edge structures and fine details, bilateral filtering is finally applied selectively to the identified flat regions. This hybrid approach achieves efficient denoising without compromising significant visual features by combining spatially adaptive filtering with multi-resolution analysis. The traditional bilateral filtering often results in over-smoothing of the edges present in the image. DWT on the other hand reduces noise very effectively but may leave ringing effects in high textured areas. To cover these limitations, the WGEAD uses a combination of DWT and Selective Bilateral Filtering(as shown in fig 1).

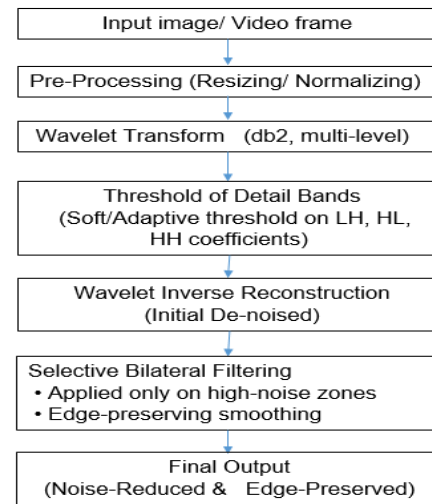


Fig 1. Working of the Proposed WGEAD Algorithm

The Discrete Wavelet Transform Approximation and detail Coefficients calculation is conducted using equation 1,2:

$$A_j[n] = \sum_k x[k] \cdot h[2n - k] \quad 1$$

$$D_j[n] = \sum_k x[k] \cdot g[2n - k] \quad 2$$

Here $A_j[n]$ = approx coefficient

$D_j[n]$ = detail coefficients

g = high-pass filter

h = low-pass filter

The workflow of the proposed model is presented below:

Algorithm: Wavelet Guided Edge Aware De-Nosing Algorithm

Input : Noise Image

Output: De-noised Image

Step 1: Preprocessing the image

- 1.1 Examine the noisy RGB picture (I).
- 1.2 Make the image 224 x 224 pixels.
- 1.3 Adjust pixel intensities to the ([0,1]) range.

Step 2: Wavelet Decomposition

2.1 Apply the Discrete Wavelet Transform (DWT) to every image channel.

2.2 Determine the detail and approximation coefficients using: Approximation coefficient:

$$A_{j[n]} = \sum_k x[k], h[2n - k] \quad 3$$

Detail Coefficients:

$$D_{j[n]} = \sum_k x[k], h[2n - k] \quad 4$$

where (h) and (g) stand for high-pass and low-pass filters, respectively.

Step 3: Applying Wavelet thresholding

Using Discrete wavelet transformation on each RGB channel. Soft thresholding (eq 5) is performed with high frequency coefficients.

$$\hat{D}_j[n] = \text{sign}(D_{j[n]}) \cdot (|D_{j[n]}| - \lambda) \quad 5$$

3.2 Inverse DWT is used to make a de-noised image I'. Noise is removed while edges are preserved.

Step 4. Detecting the flat region

- 4.1 The developed image I' is converted into grayscale.
- 4.2 Local variance is computed using a 5x5 window.
- 4.3 The regions where the variance is below threshold are considered as flat areas.

Step 5: Applying Selective Bilateral Filtering

5.1 Applying filtering only to pixels belongs to flat regions as they become smoother and better, textures remain exact and edges are preserved. (using eq 6)

Standard Bilateral Filtering rule:

$$W_p = \sum_{\{q \in \Omega\}} \exp\left(-\frac{\{p-q\}^2}{\{2\sigma_s^2\}}\right) \cdot \exp\left(-\frac{\{I(p)-I(q)\}^2}{\{2\sigma_r^2\}}\right) \quad 6$$

6.1 Edge aware selection

6.1 Calculate gradient magnitude $\nabla I(p)$

6.2 Calculate final pixel value using eq 7.

Novelty of proposed method:

$$I_{sel(p)} = I'(p), \text{ if } \nabla I(p) < T_e, \text{ otherwise, } I(p) \quad 7$$

Here

I(p)=original signal

I'(p)=bilateral-filtered value

$I_{sel(p)}$ =final selective output

$\nabla I(p)$ =gradient (change)

T_e =Edge Threshold

This results in the fNIRS signal's contour and slope being preserved while only non-edge areas are smoothed.

Step7: Output Image

In the suggested denoising framework, the identification of flat regions is crucial since it establishes the appropriate locations for smoothing operations. In this work, pixels are classified as flat or textured regions by computing a local variance measure within a sliding window. The accuracy of flat region detection and the overall de-noising performance are strongly influenced by the choice of window size.

A number of neighborhood sizes, including 3x3, 5x5, 7x7, and 9x9, were experimentally assessed in order to determine the ideal window size. Smaller windows, like 3x3, offer less spatial context and may result in erratic variance estimates, which can cause textured areas to be mistakenly classified as flat. Larger windows, like 7x7 or 9x9, on the other hand, incorporate more surrounding pixels but may oversmooth fine structural details and raise computational costs. According to experimental findings, a 5x5 window offers a fair trade-off between local image structure preservation and precise flat region detection.[12](as shwon in table 2).

Table 2.
Window Size's Impact on De-noising Effectiveness

Size of the Window	PSNR	SSIM	Time of Process
3*3	38.7	.97	.032
5*5	40.3	0.988	0.04
7*7	39	.98	0.061
9*9	37.6	0.972	0.083

To evaluate the performance of the proposed de-noising method, Gaussian noise was artificially added to the test images to simulate realistic sensor noise conditions. A noise level with standard deviation $\sigma = 15$ was used, which represents moderate noise commonly observed in digital imaging systems. All images were resized to 224×224 pixels and normalized to the range $[0,1]$ before processing. The performance of the proposed method was evaluated using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) metrics[14]. The complexity of proposed model is $O(Nk^2)$.

Returns the de-noised image with better quality.

A. Key Features of Proposed Work

- 1) The Proposed Algorithm reduces the global noise without suppressing the structured information. Authors and Affiliations.
- 2) Local high and low variance map is computed by analyzing the small neighborhoods intensity which helps in performing different types of smoothing.
- 3) Selective smoothing is applied in flat regions as these regions have minimal structure details.
- 4) Selective approach also minimizes the computational cost.
- 5) This also prevents extra blurring of the image.
- 6) To preserve texture information and edges, minimum smoothing is applied.
- 7) The proposed algorithm is adaptable across different datasets.
- 8) The final output is a refined version of input image with shape, smooth and edge-preserved images.

IV. EXPERIMENTAL SETUP AND RESULTS

a. Software and Hardware requirements:

The proposed method was developed using these setups:

Software: Python

Operating System: Windows 10

Processor: Intel Core i5

RAM: 8 GB

These configurations give stable and reproductive results.

b. Parameter Setting:

Db4 type of wavelet was used with decomposition level of

Type of thresholding: Soft thresholding

Selection of thresholding: Universal thresholding

Selective Bilateral Filtering Parameters:

Spatial Parameter = 3

Intensity Parameter = 15

Filtering Parameter = 5×5

All these parameters were chosen for balancing sharpness and smoothing of image.

c. Evaluation Metrics

To show the effectiveness of the proposed hybrid de-noising method, it is necessary to measure how well the proposed algorithm works in removing noise without hampering the important details and basic structure of the image.

PSNR and SSIM help in comparing the proposed approach with existing methods. These metrics are required as performing only visual inspection cannot determine the efficiency of the proposed model.

1. PSNR (Peak Signal to Noise Ratio)

Higher PSNR shows better reduction of noise.

$$PSNR = 10 \log_{10} \log_{10} \left(\frac{MAX^2}{MSE} \right) \quad 8$$

In this Max i represents the image's maximum pixel value, which in 8-bit pictures is 255.

MSE is the square error between the developed image (I') following de-nosing and the original image (I).

2. SSIM (Structured Similarity Index) measures the quality of the de-noised image on the bases of structure, lamination and contrast. If the value of the measure is close to 1 means the new image is similar to the original one.

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad 9$$

Here x is original image and y is de-noised image

μ is used to find the mean of x and y. σ is used to calculate variance of x and y. C represents constant.

Table 3. Experimental Conditions

Conditions	Values
Gaussian Type Noise	$\sigma = 15$
Image Size	224*224
Performance Metrics	PSNR, SSIM
Platform	Python

Visual Comparison:

The proposed model successfully reduces rain streaks while maintaining fine edges, improves illumination and structural details, as shown in the visual comparison demonstrates below in figure 2.



Fig 2. Comparision of the Proposed Model on Rain Degraded Image

To futher compare the performance of proposed WGEAD algorithm with standard methods, experiments were conduced using standard images- Cameraman (as shown in Figure 3). These images were first denosied using Gaussian noise and then restored using standard , hybrid and proposed denosing methods.

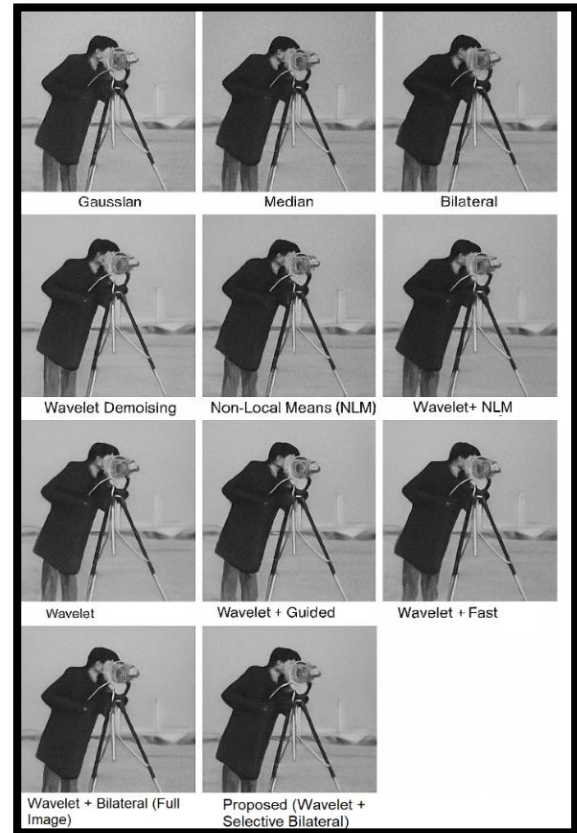


Fig 3. Performance comparison on Cameraman Image using standard, hybrid, proposed WGEAD Algorithm.

The proposed de-noising algorithm shows superior visual quality as compare to other methods.

Comparative result

To evaluate the performance of the proposed method, comparisons was conduced with existing approaches as shown in Table 4. Gaussian noise with a standard deviation of $\sigma = 15$ was used to assess the de-noising performance.

Table 4. Showing the comparison of different approaches

Method	PS NR	SSIM	Time (sec)	Edge Preservation	Notes
Gaussian Filter	30.82	0.921	0.010	Poor	Fast but blurs edges
Median Filter	31.46	0.933	0.095	Poor	Slower, blurs edges
Wavelet De-noising	36.91	0.962	0.124	Fine	Great quality + fast
Non-Local Means (NLM)	38.72	0.975	0.412	Excellent	Very slow, not real-time friendly
Hybrid (Wavelet+ NLM)	39.64	0.982	0.371	Excellent	Good quality, slowing
Wavelet + Guided Filter	37.11	0.969	0.060	Excellent	Good balance, fast
Hybrid (Wavelet+ Fast Filter)	40.1	0.985	0.091	Excellent	Combines wavelet accuracy + fast edge-preserving filter, balanced speed & quality
Wavelet + Bilateral (Full Image)	38	0.977	0.06	Excellent	Combines wavelet accuracy + bilateral filter, fast speed & balanced quality
Proposed (Wavelet + Selective Bilateral)	40.3	0.988	0.04	Excellent	Combines wavelet accuracy + selective bilateral filter, good speed & quality

The study shows significant improvement in reduction of noise and preservation of textural details. SSIM value shows the approach successfully passes in maintain the basic structure of original image.

V. CONCLUSION AND FUTURE WORK

The proposed WGEAD work is simple and robust integrating DWT with selective bilateral filtering. The WGEAD approach firstly handles high frequency noise using wavelet decomposition with soft thresholding without harming structure information. The selective bilateral filtering smooths the required texture regions without blurring edge important details. The combined results give better quality of image with edge preservation and superior PSNR, SSIM value compared to wavelet and bilateral filtering alone. Additionally, computational cost is remains low, making it reliable and efficient. All these makes, the proposed WGEAD model easy to integrate with real time computer vision applications for analysis. In future work can be directed towards multi scale bilateral filtering and may extend the method to image de-hazing and related task application.

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