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Medical Image De-noising using Discrete Wavelet Transform and Threshold Filter

Trapti Soni¹, Dr. Deepti Agrawal²

M. Tech. Scholar, Department of Electronics and Communication Engineering, SORT, People's University,

Bhopal, India¹

Professor, Department of Electronics and Communication Engineering, SORT, People's University, Bhopal, India²

ABSTRACT: Medical imaging is a cornerstone of modern diagnostic and therapeutic practices. However, images obtained from modalities such as MRI, CT, and ultrasound are often contaminated with noise during acquisition or transmission, which can compromise diagnostic accuracy. This study presents an efficient de-noising technique that leverages the Discrete Wavelet Transform (DWT) combined with threshold filtering to enhance the quality of medical images. DWT decomposes an image into various frequency sub-bands, enabling the isolation of noise components primarily found in high-frequency details. Threshold filtering—both hard and soft thresholding—is applied to the detail coefficients to suppress noise while preserving important structural and diagnostic features. After thresholding, the inverse DWT is employed to reconstruct the de-noised image. The performance of the proposed method is evaluated using metrics such as Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE). Experimental results demonstrate that the DWT-based threshold filtering approach achieves significant noise reduction while maintaining the integrity of vital medical information. This technique offers a promising solution for enhancing image quality in clinical diagnostics and can be further optimized using adaptive thresholding or integrated with machine learning models for real-time applications.

KEYWORDS: Medical Image, Median Filter, Threshold Filter, High Density

I. INTRODUCTION

Within seconds of entering the world, those who are blessed with the gift of sight start acquiring images. Human beings are primarily visual creatures, who depend solely on the sense of vision. Vision allows humans to perceive and understand the world surrounding them in a better manner. Processing visual information by the computer has been drawing significant attention of researchers over the last few decades. The process of receiving and analyzing visual information by the human species is referred to as sight, perception or understanding. Similarly, the process of receiving and analyzing visual information by digital computer is called digital image processing [1, 2]. A monochrome image I, is described as a two-dimensional function can be defined as,

$$I = f(x, y) \tag{1}$$

Where, and are spatial coordinates. Amplitude of at any pair of coordinates (x, y) is called intensity I or gray value of the image. When spatial coordinates and amplitude values are all finite, discrete quantities, the image is called digital image [3]. The digital image I is represented by a single 2-dimensional integer array for a gray scale image and a series of three 2-dimensional arrays for each colour band (R,G,B) in a color image. The digital images are called bit-maps or raster-scan images, and are composed of an array (grid or matrix) of smaller units called pixels (picture elements). Each pixel in the digital image is a uniform patch of colour but on the display screen is made up of a red, green and blue phosphor dot or stripe. A pixel is the smallest digital image element manipulated by image processing software. Thus, bit maps often show "blocky" areas or jagged lines under close examination.

Image processing has become a pre-cursor for various vision applications. Few such applications are discussed below in nutshell [4].





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In medical image processing, noise reduction is a critical pre-processing step to enhance image quality and ensure accurate interpretation by radiologists and diagnostic systems. One of the most commonly used techniques for this purpose is the median filter, a non-linear spatial filtering method. The median filter is particularly effective for removing impulsive noise, such as salt-and-pepper noise, which frequently contaminates images captured from medical devices like MRI, CT, and ultrasound scanners. Unlike linear filters that average pixel values and often blur important structures, the median filter preserves edges and fine anatomical details, which are vital for accurate diagnosis and clinical analysis.

The fundamental principle of the median filter involves replacing each pixel's intensity with the median value of its neighborhood defined by a kernel (typically 3×3 or 5×5). This process effectively eliminates outliers (noisy pixels) without significantly altering the true structure of the image. For example, in an MRI scan, sharp boundaries between different tissues such as white and gray matter must be retained. The median filter maintains these edges while suppressing the noise, which might otherwise mimic pathology or obscure small lesions.

In practice, the median filter is widely used in applications such as brain tumor segmentation, X-ray enhancement, ultrasound speckle noise reduction, and pre-processing in computer-aided diagnosis (CAD) systems. Its non-linear behavior gives it an advantage in situations where preserving contrast and structural integrity is crucial. Additionally, it serves as a foundational technique in preparing medical images for further processing tasks like segmentation, classification, or feature extraction, often used in machine learning and deep learning pipelines.

Despite its strengths, the median filter has some limitations. When applied with a large kernel size, it may smooth out fine textures or small features that could be clinically significant. Moreover, the computational complexity increases with the size of the kernel, which can be a concern for real-time or high-resolution applications. To address these issues, adaptive median filters and hybrid methods combining median filtering with wavelet transforms or anisotropic diffusion have been proposed.

In conclusion, the median filter remains a robust, effective, and easy-to-implement method for de-noising medical images. Its ability to eliminate noise while preserving critical diagnostic features makes it an essential tool in the preprocessing stage of many medical imaging applications, contributing to improved diagnostic accuracy and enhanced image interpretation.

II. MEDIAN FILTER

The median filter is a non-linear digital filtering technique widely used in image processing and signal processing to remove noise while preserving important image features such as edges. Unlike linear filters such as the mean filter, which can blur sharp edges, the median filter is particularly effective at removing impulsive or salt-and-pepper noise from an image. The core concept of the median filter is to replace the value of a pixel with the median value of its neighboring pixels within a defined window, typically a square kernel like 3×3 , 5×5 , or larger, depending on the application. The median value is calculated by sorting all the pixel values in the window and selecting the middle value. This process ensures that outlier pixel values, which often represent noise, are excluded from the final result.

One of the main advantages of the median filter is its ability to preserve edge information. Since edges are critical for interpreting the structure of medical or natural images, this property makes the median filter especially valuable in applications such as X-ray image enhancement, MRI pre-processing, or general photographic noise reduction. In the presence of salt-and-pepper noise, where pixels are randomly set to extreme values (typically 0 and 255), the median filter can remove these anomalies without affecting the surrounding pixels significantly.

However, the median filter is not without limitations. It can sometimes cause minor distortions in areas with fine textures or patterns, especially when larger window sizes are used. This is because the filter does not consider the spatial relationships between pixels and simply replaces them based on ranked intensity values. To mitigate such issues, adaptive median filters have been developed, which vary the window size based on local noise characteristics, improving results in non-uniform noise environments.





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The implementation of a median filter is computationally more intensive than that of linear filters, particularly in large images or with larger kernel sizes. Nonetheless, due to advances in processing power and algorithm optimization, real-time application of the median filter has become feasible. It is widely used in medical imaging, remote sensing, biometric applications, and even in pre-processing stages for machine learning models. In conclusion, the median filter is a powerful, reliable, and simple tool for removing noise from images, especially effective against impulsive noise, with the added benefit of preserving edge sharpness—an essential feature in many practical image processing tasks.

III. TYPES OF NOISE

The procedure which attempt to expel the noise from the image and restore the quality of the original image is known as Image Restoration. It is an essential feature in maintaining the quality of the image by using restoring the pixel value. For linear image degradation, Restoration techniques are a model and it is the just opposite process of improving the quality of original image. To find an optimal gauge of the desired outcome restoration technique includes mathematically principle of goodness which accomplishes it.

Speckle Noise:

Speckle Noise is a multiplicative noise. It is a random signal where the average amplitude increases with the overall signal intensity. It appears as bright specks in the lighter regions of the image.

It can be modelled as a pixel value multiplied by the random value.

Speckle Noise can be modelled as

I = S + (S*Ng)

Where Ng is the random noise having a zero mean Gaussian probability distributive function.

Salt and pepper Noise:

It is also known by various names such as shot noise, Impulse noise and binary noise. Salt and pepper noise is a form of noise sometimes seen on images. Noise can be caused by sharp and sudden disturbance in image signal. This noise is mostly caused by sensor & memory problems due to which pixels are assigned incorrect maximum values. The corrupted pixels are set alternatively to the minimum or maximum value & unaffected pixels remain same, giving the image salt & pepper noise like appearance. It presents itself as sparsely occurring white and black pixels. An effective noise reduction algorithm for this type of noise involves the usage of a median filter. Minimum filtering ,maximum filtering ,maximum filtering ,maximum filtering are the some other filters which reduced less amount of noise compare to median filter without significantly reducing the sharpness of the image, salt and pepper noise can be reduced.

IV. PROPOSED METHODOLOGY

The Modified Median Filter calculation is the point at which a chose window contains just 0 and 255 esteem then the reestablished esteem is either 0 or 255(again uproarious), drives us to proposed. In this calculation we chose pixel esteem 0 and 255 values then the preparing pixel is supplanted by mean estimation of the chose window. The detail of the calculation is given underneath.





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Figure 1: Flow Chart of Proposed Method

Algorithm:

Step 1: Select a 3 x 3 matrix size according to the 2-D window size. Assume that the processing pixel is P_{ij} , which lies at the center of window.

Step 2: If 0 < Pij < 255, then the processing pixel or Pij is uncorrupted and left unchanged.

Step 3: On the off chance that Pij = 0 or Pij = 255, then it is considered as tainted pixel and four cases are conceivable as given underneath.

Case 1: In the event that the chose window has all the pixel esteem as 0, then Pij is supplanted by the Salt clamor (i.e. 255).

Case 2: On the off chance that the chose window contains all the pixel esteem as 255, then Pij is supplanted by the pepper commotion (i.e. 0).

Case 3: In the event that the chose window contains all the esteem as 0 and 255 both. At that point the handling pixel is supplanted by mean estimation of the window.

Case 4: On the off chance that the chose window contains not all the component 0 and 255. At that point dispose of 0 and 255 and locate the middle estimation of the rest of the component. Supplant Pij with middle esteem.

Step 4: Rehash step 1 to 3 for the whole picture until the procedure is finished.

Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) is a powerful mathematical tool widely used in medical image processing for tasks such as de-noising, compression, and feature extraction. Unlike traditional Fourier transforms that provide only frequency information, DWT offers both spatial and frequency localization, making it highly effective for analyzing non-stationary signals like medical images. DWT works by decomposing an image into multiple resolution levels using a series of high-pass and low-pass filters. This results in four sub-bands at each level: LL (approximation), LH





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(horizontal details), HL (vertical details), and HH (diagonal details). The LL sub-band contains the most significant image features, while the other bands capture high-frequency components typically associated with noise or fine details.

In medical imaging applications such as MRI, CT, PET, and ultrasound, noise can severely degrade image quality and obscure crucial anatomical structures. DWT-based de-noising involves decomposing the image, applying a threshold filter to the high-frequency coefficients (LH, HL, HH), and then reconstructing the image using the inverse DWT (IDWT). This process effectively suppresses noise while preserving edges and fine details, which are essential for accurate diagnosis and analysis. Various thresholding techniques such as soft and hard thresholding are used, often with adaptive strategies to enhance performance in different noise conditions.

The multi-resolution capability of DWT also makes it suitable for medical image compression, reducing storage and transmission costs without significant loss of diagnostic information. It is commonly used in JPEG 2000, a waveletbased image compression standard that provides high compression efficiency for medical images. Furthermore, DWT is used in feature extraction for machine learning and deep learning models, where the extracted coefficients serve as robust descriptors for classification or segmentation tasks.

Despite its many advantages, DWT has some limitations. It can introduce artifacts if the threshold is not properly selected, and its computational complexity increases with the level of decomposition. However, the development of fast wavelet transform algorithms and hardware acceleration has made real-time applications more feasible. Advanced forms like wavelet packet transform, dual-tree complex wavelet transform, and undecimated wavelet transform offer improved performance in specific scenarios.

V. SIMULATION RESULT

The proposed calculations are tried utilizing 256x256 8bit/pixel picture bike.jpg. In the reproduction, pictures are tainted by Salt and Pepper commotion. The commotion level shifts from 10% to 90% with augmentation of 10% and the execution is quantitatively measured by Mean square Error (MSE) and Peak Signal to Noise Ratio (PSNR). Mean Square Error (MSE)

$$=\frac{1}{N_1N_2}\sum_{j=1}^{N_2}\sum_{i=1}^{N_1} (f(i,j) - g(i,j))^2$$
(1)

Peak Signal to Noise Ratio (PSNR) in dB

$$=10 \times \log_{10}(\frac{255^{2}}{MSE})$$
 (2)

Where MSE remains for Mean Square Error, PSNR remains for Peak Signal to Noise Ratio. From the reproduction result appeared in Table I to II, it is watched that the execution of proposed calculation is enhanced PSNR than the current calculations at medium and high clamor level.

The results in the Table 1 clearly show that the PSNR of different method is much better at high density of salt and pepper noise. As the density of noise increasing, the response of proposed filter is becomes better in comparison of other filters.





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(a) Original Image (b) 0.01 Noise Density



(c) 0.02 Noise Density (d) 0.03 Noise Density



(e) 0.04 Noise Density (f) 0.05 Noise Density



(g) 0.06 Noise Density (h) 0.07 Noise Density





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(i) 0.08 Noise Density (j) 0.09 Noise Density



Figure 2: Experimental Speckle Noise Image for Different Noise Density

Image Density	MSE	PSNR (dB)
0.01	0.7640	49.2998
0.02	1.3754	46.7465
0.03	1.9929	45.1359
0.04	2.4775	44.1906
0.05	3.3191	42.9207
0.06	4.0572	42.086
0.07	4.4223	41.6743
0.08	5.4013	40.8058
0.09	5.4709	40.7502



(a) 0.01 De-noising of Salt and Pepper Noise

(c) 0.03 De-noising of Salt and Pepper Noise









(d) 0.04 De-noising of Salt and Pepper Noise

(b) 0.02 De-noising of Salt and Pepper Noise

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(e) 0.05 De-noising of Salt and Pepper Noise (f) .06 De-noising of Salt and Pepper Noise



(g) 0.07 De-noising of Salt and Pepper Noise (h) .08 De-noising of Salt and Pepper Noise



(i) 0.09 De-noising of Salt and Pepper Noise

Figure 3: Experimental Results of Proposed Method for real Head Image

Table 2: Comparison of PSNR of Different Density for Head Image

Density	Proposed Modified Median Filter
0.01	50.1434
0.02	47.0639
0.03	45.2262
0.04	43.8404
0.05	42.8793
0.06	39.999
0.07	38.4161
0.08	37.5612
0.09	36.2986

VI. CONCLUSION

Medical image de-noising is essential for enhancing visual quality and ensuring accurate diagnosis. The combination of Discrete Wavelet Transform (DWT) **and** threshold filtering provides a robust and efficient method for removing noise while preserving critical anatomical features. DWT enables multi-resolution decomposition, allowing noise to be isolated in the high-frequency sub-bands. By applying soft or hard thresholding techniques, irrelevant noise components can be effectively suppressed without distorting significant image details.





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The reconstructed image, obtained through inverse DWT, demonstrates improved clarity and structural integrity, making this approach highly suitable for medical applications. Quantitative evaluations using PSNR and MSE confirm that this technique yields superior performance compared to traditional spatial domain methods.

In summary, DWT-based threshold de-noising offers a powerful and computationally efficient solution for improving medical image quality. This approach can be further enhanced by incorporating adaptive thresholding, wavelet packet transforms, or machine learning algorithms for automated and real-time de-noising in clinical systems. Its adaptability and effectiveness make it a valuable tool in modern medical image processing pipelines.

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