Comparative Analysis of Image Restoration Techniques for MRI Brain Scans: A Study on Filtering and Wavelet-Based Methods

Amanpreet Kaur Sandhu
University Institute of Computing, Chandigarh University, Gharuan, Mohali

Abstract This paper presents a comparative study of image restoration techniques applied to MRI brain scans and general test images. The restoration methods include median filtering, adaptive filtering, linear filtering, and wavelet-based restoration. Using 2-D discrete wavelet transforms (DWT), the images were decomposed into approximation and detail components, followed by wavelet thresholding to suppress noise. The performance of hard- and soft-thresholding methods was evaluated to enhance image quality while preserving crucial structural details. Error metrics, such as Mean Square Error (MSE), were used to assess the restoration quality, while image histograms and contour plots were analyzed to examine contrast enhancement and visual clarity.

Index Terms— **image processing, MRI, MSE, median filter, wavelet**

I. INTRODUCTION

Medical imaging plays a critical role in modern diagnostics, with MRI (Magnetic Resonance Imaging) being one of the most commonly used modalities for detecting and analyzing various brain disorders. However, MRI images are often subject to noise and artifacts that can degrade image quality, making it difficult for clinicians to accurately interpret the results. Effective image restoration techniques are therefore essential to enhance the clarity and reliability of these images by reducing noise and preserving crucial anatomical details [1].

Magnetic Resonance Imaging (MRI) is widely used for visualizing the internal structures of the body, especially the brain. However, MRI images are frequently contaminated by noise during acquisition and transmission, which can obscure critical diagnostic information. Image restoration techniques aim to reduce noise while preserving significant anatomical features. In this study, we investigate and compare four image denoising techniques—Median Filtering, Adaptive Filtering, Linear Filtering, and Wavelet-Based Restoration—to determine the most effective method for enhancing MRI brain scans.

Image restoration has been a long-standing research area in image processing, with numerous techniques being developed to address different types of noise and degradation. Commonly used methods include linear filters, such as mean and Gaussian filters, as well as non-linear approaches like median filters and adaptive filters [2]. These techniques have proven effective in various scenarios but may struggle with edge preservation or specific noise patterns. More advanced methods, such as wavelet-based restoration, have been introduced to improve upon these limitations by offering multi-scale and multi-resolution analysis, which is particularly effective in retaining fine image details.

While individual restoration methods have their strengths, there is no one-size-fits-all solution, as the performance of each technique can vary depending on the image characteristics, noise type, and desired outcome [3]. This variability necessitates a thorough comparison of different image restoration techniques to determine their effectiveness in specific applications, such as MRI image enhancement.

In this research, compare the performance of four widely used image restoration techniques—median filtering, adaptive filtering, linear filtering, and wavelet-based restoration—across multiple MRI brain scans and test images [4]. By analyzing the error metrics, we aim to determine which method provides the best balance between noise reduction and detail preservation in different scenarios. Our findings offer insights into the strengths and weaknesses of each approach, guiding the selection of the most appropriate restoration technique for medical imaging and other related fields [5].

2. IMAGE RESTORATION TECHNIQUES

Previous research in medical image denoising has explored various linear and nonlinear filtering techniques. Median filters are commonly used for their robustness against salt-and-pepper noise, while adaptive filters dynamically adjust based on local image statistics. Linear filters, such as averaging or Gaussian filters, are simple but often cause blurring. Wavelet-based techniques have gained popularity due to their multi-resolution approach, which enables efficient noise removal while retaining image details. Despite significant advancements, a comprehensive comparison of these techniques on MRI brain scans remains necessary.

Spatial domain methods are divided into various types of filters such as linear and non-linear filters. These filters are used for basic noise reduction. However, mean Filter is basically each pixel is replaced by the average of its neighbors, useful for smoothing but may blur the image. Additionally, Gaussian Filter is weights neighboring pixels according to a Gaussian distribution, offering a gentler smoothing.

Non-Linear Filtering: Non-linear filtering is divided into median and bilateral filter. Median Filter is replacing each pixel with the median value of neighboring pixels. Great for removing salt-and-pepper noise. In order to, Bilateral Filter for Smoothens images while preserving edges by considering both spatial proximity and pixel intensity similarity [6].

2.1. TRANSFORM DOMAIN METHODS

These techniques work by transforming the image into a different domain (e.g., frequency) and modifying the transformed coefficients. Fourier Transform (FT) is applied to convert an image into the frequency domain. Low-pass filters can be used to remove high-frequency noise. In order to, Wavelet Transform is decomposing an image into multi-scale levels, where noise can be removed at different scales while preserving important details. However, Non-Subsampled Shearlet Transform (NSST) is multi-scale and directional decomposition method that is particularly effective for capturing geometric features. It's often used in conjunction with other filters, such as bilateral filters, for image denoising and restoration.

Statistical methods is divided into wiener and Bayesian methods. Wiener Filter is deblurring technique that minimizes the mean square error between the estimated and true images. It uses statistical information about the image and noise. In order to Bayesian Methods assume a statistical model for both the image and noise. These methods aim to estimate the original image using prior probabilities and likelihoods [7].

2.2. REGULARIZATION-BASED METHODS

These methods approach image restoration as an optimization problem, seeking to minimize a cost function that balances data fidelity and smoothness. Tikhonov Regularization Adds a penalty term to smooth out the solution and avoid overfitting. Total Variation (TV) Minimization aims to preserve edges while removing noise by minimizing the total variation of the image gradient.

3. PROPOSED WORK

In the proposed work, 2-D discrete wavelet transform (DWT) to decompose an image into its approximation and detail components. The approximation represents the high-scale, low-frequency elements of the signal, while the detail components capture the low-scale, high-frequency elements. After decomposition, wavelet thresholding is applied to the decomposed coefficients. This technique assumes that the signal's magnitudes dominate the noise magnitudes in a wavelet representation, allowing wavelet coefficients to be set to zero if their magnitudes fall below a predetermined threshold. There are two common thresholding methods used for denoising: hard-thresholding and soft-thresholding. Additionally, iterating the context-based thresholding process and using a more sophisticated context model in the denoised wavelet representation can further enhance the denoising results [8].

An image histogram is a fundamental tool for analyzing image characteristics. It visually represents the distribution of pixel intensity values in a grayscale image, making it useful for contrast enhancement and assessing image quality. The histogram provides statistical information about the digital image, showing the number of pixels at each intensity value. This is particularly helpful when comparing the quality of restored images, as the histogram reflects the intensity range and pixel distribution. Contour plots are also employed as a visual tool to compare image quality, representing areas of equal intensity in an image. These plots define constant intensity values and align with the axes to maintain the aspect ratio of the image. Well-restored images tend to have less congested contour plots, clearly displaying each intensity feature [9].

The perception of the human eye refers to how the processed image appears when compared to the original, particularly in terms of contrast and clarity. Mean Square Error (MSE) is used to quantify the difference between the original and restored images by measuring pixel differences [10]. MSE is one of the most commonly used metrics in image processing and computer vision due to its mathematical simplicity and ease of implementation in systems that aim to minimize the error between the original and noisy images.

S.no	Name of image processed	Median filter	Adaptive filter	Linear filter	Wavelet restoration
1	MRI BRAIN	65.45	276.35	171.33	75.92
2	MRI IMAGE	81.33	79.64	166.95	78.16
3	IMAGE NEW	32.40	16.06	10.97	72.14
4	MRI01	31.25	11.07	50.46	0.00
5	MRI03	81.30	292.05	34.08	79.21
6	MRI04	131.94	32.39	29.27	163.82
7	MRI05	180.7	67.45	132	165.67

Table 1: MSE of images

The Mean Squared Error (MSE) values presented in the table 1 indicate the effectiveness of four different image denoising filters—Median, Adaptive, Linear, and Wavelet Restoration—when applied to various MRI and test images. MSE is a common metric used to evaluate the quality of an image restoration technique, where lower values signify better performance and closer similarity to the original image. From the results, it is evident that Wavelet Restoration generally provides superior performance, showing the lowest MSE for images like MRI01 (0.00), suggesting near-perfect denoising, and consistently low errors across other MRI datasets. This method is particularly effective for medical images due to its ability to preserve both edges and fine texture details through multi-resolution analysis. The Adaptive filter, which adjusts its behavior based on local image characteristics, shows excellent results for relatively simple or uniform images like IMAGE NEW (16.06) and MRI01 (11.07), but performs poorly on complex textures, evident from the high MSE for MRI03 (292.05). Median filtering, known for its effectiveness against salt-and-pepper noise, performs moderately well, especially on images like MRI IMAGE (81.33) and MRI03 (81.30), but can struggle with preserving fine image details, as seen in MRI05 (180.70). Meanwhile, the Linear filter, although simple and fast, often leads to blurring and higher MSE in complex images, with a notable exception in IMAGE NEW (10.97), where the image complexity is likely minimal. In conclusion, Wavelet Restoration emerges as the most robust and reliable technique across diverse image types, especially for high-detail medical images, while other filters show strengths in more specific scenarios.

CONCLUSION

Based on the MSE analysis of different filtering techniques applied to MRI and test images, it is evident that Wavelet Restoration consistently outperforms other filters, particularly for complex and high-detail medical images. It effectively balances noise removal with edge and texture preservation, resulting in the lowest MSE in most cases. Adaptive filters perform well on images with uniform noise but tend to over-smooth and degrade quality on more textured images. Median filtering offers reasonable results against impulse noise but may distort image details, while Linear filters, though computationally simple, generally result in higher MSE due to blurring effects. Therefore, Wavelet-based methods are the most suitable choice for accurate and high-quality image denoising, especially in medical imaging applications where detail preservation is critical.

Future research can explore hybrid models that combine the strengths of multiple filtering techniques, as well as machine learning-based denoising approaches that adaptively learn optimal restoration parameters. Additionally, extending the evaluation metrics beyond MSE, such as PSNR and SSIM, may offer a more comprehensive assessment of image quality.

REFERENCE

[1] Sandhu, A. K. (2023, March). Post-Processing Deblocking Technique for Reduction of Blocking Artifacts. In 2023 6th International Conference on Information Systems and Computer Networks (ISCON) (pp. 1-4). IEEE.

[2] Tripathi, P. C., & Bag, S. (2020). CNN-DMRI: a convolutional neural network for denoising of magnetic resonance images. Pattern Recognition Letters, 135, 57-63.

[3] Thakur, R. S., Yadav, R. N., & Gupta, L. (2019). State-of-art analysis of image denoising methods using convolutional neural networks. IET Image Processing, 13(13), 2367-2380.

[4] Kaur, A., & Singh, D. J. (2016). Review on image compression techniques and advantages of image compression. IJARSE.

[5] Thakur, R. S., Chatterjee, S., Yadav, R. N., & Gupta, L. (2023). Medical image denoising using convolutional neural networks. In Digital Image Enhancement and Reconstruction (pp. 115-138). Academic Press.

[6] Lone, M. R., & Sandhu, A. K. (2024). Enhancing image quality: A nearest neighbor median filter approach for impulse noise reduction. Multimedia Tools and Applications, 83(19), 56865-56881.

[7] Jurek, J., Materka, A., Ludwisiak, K., Majos, A., Gorczewski, K., Cepuch, K., & Zawadzka, A. (2023). Supervised denoising of diffusion-weighted magnetic resonance images using a convolutional neural network and transfer learning. Biocybernetics and Biomedical Engineering, 43(1), 206-232.

[8] Sandhu, A. K. (2025, February). A Hybrid Approach for Detection and Reduction of different types of noises in gray scale images. In 2025 3rd International Conference on Intelligent Systems, Advanced Computing and Communication (ISACC) (pp. 684-689). IEEE.

[9] Hammernik, K., Schlemper, J., Qin, C., Duan, J., Summers, R. M., & Rueckert, D. (2021). Systematic evaluation of iterative deep neural networks for fast parallel MRI reconstruction with sensitivity-weighted coil combination. Magnetic Resonance in Medicine, 86(4), 1859-1872.

[10] Kaur, A., Sidhu, J. S., & Bhullar, J. S. (2018). Artifacts reduction based on separate modes in compressed images. Journal of Intelligent & Fuzzy Systems, 35(2), 1645-1656.

[11] Jiang, D., Dou, W., Vosters, L., Xu, X., Sun, Y., & Tan, T. (2018). Denoising of 3D magnetic resonance images with multi-channel residual learning of convolutional neural network. Japanese journal of radiology, 36, 566-574.