Mitigating Noise from Biomedical Images Using Wavelet Transform Techniques

Asadullah Bin Rahman[1] Masud Ibn Afjal[2] Md. Abdulla Al Mamun[3]

[1,2,3]Department of Computer Science and Engineering
Hajee Mohammad Danesh Science and Technology University, Dinajpur-5200, Bangladesh

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Introduction

Biomedical Images:

- MRI
- CT Scan
- X-ray, etc

Noise in Images:

- Thermal noise from the patient's body
- Electronic Components
- Interference from outside environment

Effects of Noise:

- May lead to incorrect Region of Interst (ROI)
- Trouble to human eyes, difficult for doctors and radiologists for proper diagnosis
- Difficulty in machine learning

Problem Statement:

Medical images are often corrupted by noise during acquisition and processing. Traditional denoising methods struggle with complex noise patterns, leading to loss of important details. This study aims to optimize wavelet-based denoising to enhance image clarity.

Research Objectives

- Identify the optimal wavelet and thresholding method for MRI denoising.
- Evaluate denoising performance using PSNR, MSE, and SSIM.
- Lay the foundation for hybrid wavelet-deep learning approaches.

Related Works

Table: A few most recent & relevant state-of-the-art methods

Previous Work	Authors	Method	Year
Image denoising for magnetic resonance imaging medical images using improved generalized cross-validation based on the diffusivity function	S. Kollem, K. Ramalinga Reddy, D. Srinivasa Rao, C. Rajendra Prasad, V. Malathy, J. Ajayan, and D. Muchahary,	Quaternion Wavelet Transformation, Partial Differential Equation	2022
Efficient denoising of multi-modal medical image using wavelet transform and singular value decomposition	R. Patil and S. Bhosale	Wavelet Transform (WT), Singular Value Decomposition(SVD)	2023
A study of adaptive fractional-order total variational medical image denoising	Y. Zhang, T. Liu, F. Yang, and Q. Yang,	Mathematical (Total Variation Denoising)	2022
Efficient deep-learning-based autoencoder denoising approach for medical image diagnosis	W. El-Shafai, S. A. El-Nabi, E.-S. M. El-Rabaie, A. M. Ali, N. F. Soliman, A. D. Algarni, and F. E. A. El-Samie	Deep Learning Autoencoder	2022
Medical image denoising using convolutional denoising autoencoders	L. Gondara	Deep Learning Autoencoder	2016

Research Questions

- Which wavelet type and thresholding method achieve the best denoising performance?
- What decomposition level offers an optimal balance between noise reduction and detail preservation?
- How do different thresholding techniques impact image quality?

Proposed Methodology

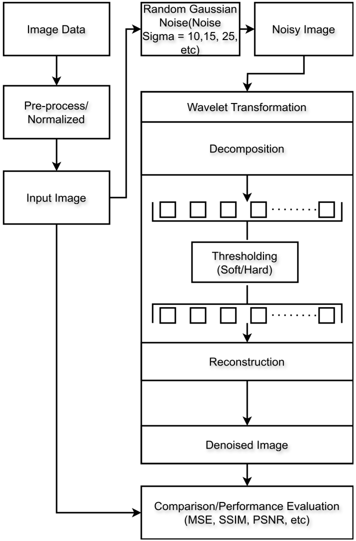


Figure: A detailed system flowchart

Experimental setup

Noisy Image:

- $\mu = 0, \sigma = 10, 15, 25$

Denoised Image:

- Decomposition upto level 5
- Wavelet used: db3, bior6.8, and sym4
- Optimal threshold (τ_{bayes}) and ($\tau_{universal}$) was estimated using the Bayes and Universal method
- Thresholding method: hard and soft

Experiments

Table: Noise settings used in the experiments

Exp. no	Noise Setup			
	Noise standard deviation (σ)	MSE	SSIM	PSNR
1	10	761.108	0.5	19.316
2	10	725.131	0.493	19.527
3	15	1148.059	0.385	17.531
4	15	1492.804	0.373	16.391
5	25	2513.741	0.252	14.128
6	25	2901.145	0.259	13.505

Table: Optimal denoising configurations and observed metrics

Exp. no	Optimal Denoising Configuration with Observed Metrics						
	Decomposition level	Wavelet	Thresholding value	Thresholding method	MSE	SSIM	PSNR
1	2	sym4	τ_{bayes}	hard, soft	105.297	0.782	27.907
2	4	db3	$\tau_{universal}$	soft	78.128	0.784	29.203
3	2	sym4	τ_{bayes}	hard, soft	198.016	0.711	25.164
4	3	db3	$\tau_{universal}$	hard	108.145	0.74	27.791
5	2	sym4	τ_{bayes}	hard, soft	487.683	0.597	21.249
6	4	db3	$\tau_{universal}$	soft	196.635	0.656	25.194

Experiments (Cont.)

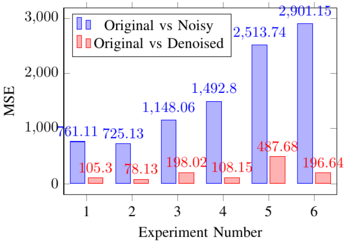


Figure: MSE

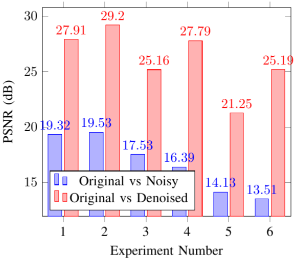


Figure: PSNR

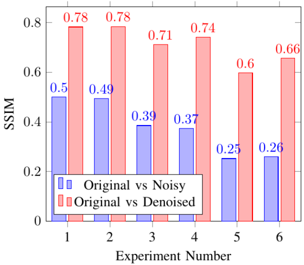


Figure: SSIM

Experiments (Cont.)

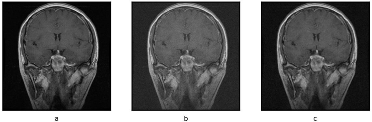


Figure: Exp. no 1

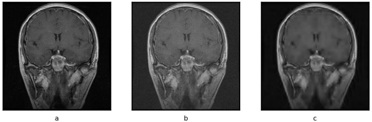


Figure: Exp. no 2

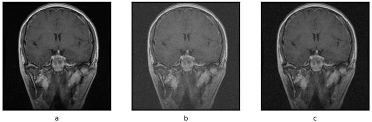
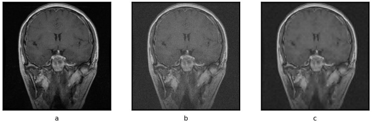


Figure: Exp. no 3



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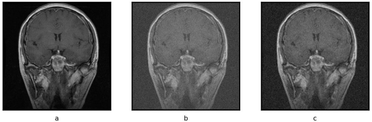

Figure: Exp. no 5

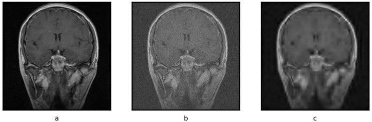

Figure: Exp. no 6

Result Discussion

- The sym4 wavelet seems to work well with τ_{bayes}
- The db3 wavelet seems to work well with $\tau_{universal}$

Best performed combination: db3 with $\tau_{universal}$

σ	PSNR(dB)
10	29.203
15	27.791
25	25.194

Conclusion

- Deterministic approach
- Fast compared to the deep learning based methods
- Doesn't require training data

Future Work

- Comparison with state-of-the-art methods
- Integrating wavelet-based methods with deep learning

References

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QnA

Thank You!