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Denoising Retinal OCT Images Using Classical and Advanced Filtering Techniques

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Abstract: ***Digital image processing employs mathematical algorithms to enhance medical imaging. Retinal Optical Coherence Tomography (OCT), a non-invasive technique, offers high-resolution cross-sectional views of the retina, crucial for early detection of conditions such as glaucoma, diabetic retinopathy, and age-related macular degeneration. However, OCT images are often compromised by noise arising from acquisition, transmission, or hardware limitations, including Gaussian, salt-and-pepper, speckle, and Poisson noise, which can obscure fine retinal structures. This study systematically investigates the impact of these noise types on OCT images by artificially introducing noise and evaluating various denoising filters. Classical methods, including mean, median, and mode filters, were compared with advanced techniques such as Wiener filtering, wavelet-based denoising, and non-local means filtering, using both custom MATLAB implementations and built-in functions. Quantitative assessment was performed using Peak Signal-to-Noise Ratio (PSNR) and Signal-to-Noise Ratio (SNR). Results indicate that Wiener filtering excels in mitigating Gaussian, Poisson, and speckle noise, while median and mode filters are most effective against salt-and-pepper noise. For real OCT images, wavelet-based denoising provides an optimal trade-off between noise suppression and edge preservation. These insights inform the selection of appropriate filters for OCT image enhancement, supporting improved clinical analysis.***

Keywords: Optical Coherence Tomography (OCT), Image Denoising, Gaussian Noise, Salt-and-Pepper Noise, Speckle Noise, Poisson Noise, Wiener Filter, Wavelet Transform

1.Introduction

Optical Coherence Tomography (OCT) images are frequently degraded by various noise types, including Gaussian, Poisson, salt-and-pepper, and speckle, each affecting image quality differently. This has driven the development of diverse denoising strategies, broadly categorized into spatial filtering, statistical models, transform-based methods, patch-based approaches, and, more recently, learning-based algorithms. Early efforts focused on simple spatial filters: the mean filter reduces random intensity fluctuations but blurs edges, while non-linear filters like median and mode effectively suppress impulse noise, particularly salt-and-pepper, while preserving edge sharpness. However, these methods are less effective against Gaussian and speckle noise.

Adaptive statistical filters, notably the Wiener filter, exploit local variance to minimize mean square error, improving performance for Gaussian and Poisson noise but sometimes introducing edge blurring. Transform-based methods, such as wavelet thresholding, enable multi-scale noise suppression, preserving fine structures and anatomical edges; extensions using shearlets and curvelets enhance directional feature capture in retinal layers. Patch-based approaches, including non-local means (NLM), leverage self-similarity across image regions to achieve strong denoising while retaining texture, though at higher computational cost. For low-photon Poisson noise, variance-stabilizing transformations combined with Gaussian-based filters yield improved results.

Deep learning has recently advanced OCT denoising, with convolutional networks and hybrid models outperforming classical approaches in reducing speckle and mixed noise while maintaining structural integrity. Despite requiring substantial data and computational resources, these models offer superior image quality. Overall, the evolution from simple spatial filters to learning-based methods highlights trade-offs between noise suppression, detail preservation, and computational complexity, motivating comparative evaluations of classical and transform-based techniques as practical baselines for real-world OCT applications.

2.Literature Review

Optical Coherence Tomography (OCT) images are frequently degraded by noise types such as Gaussian, Poisson, salt-and-pepper, and speckle, each uniquely affecting image quality. This has motivated the development of diverse denoising strategies, broadly categorized into spatial filtering, statistical modelling, transform-based methods, patch-based approaches, and, more recently, learning-based algorithms. Early studies focused on simple spatial filters: the linear mean filter reduces random intensity fluctuations but blurs edges, while non-linear filters such as median and mode are effective against impulse noise, particularly salt-and-pepper, with better edge preservation. However, these filters are limited when addressing Gaussian and speckle noise.

Adaptive statistical methods, notably the Wiener filter, utilize local variance to minimize mean square error, improving performance for Gaussian and Poisson noise but sometimes causing edge blurring. Transform-based techniques, particularly wavelet thresholding, enable multi-scale noise suppression while preserving anatomical edges, with advanced transforms like shear lets and curvelets enhancing directional feature capture. Patch-based approaches, especially non-local means (NLM), exploit self-similarity across image regions to achieve strong denoising and texture preservation, though at higher computational cost and sensitivity to patch parameters. For Poisson noise, variance-stabilizing transformations combined with Gaussian-based filters improve performance in low-photon imaging conditions. More recently, deep learning methods—including convolutional neural networks, self-supervised models, and hybrid architectures—have outperformed classical approaches in reducing speckle and mixed noise while maintaining structural integrity, albeit requiring substantial data and computational resources.

Overall, the progression from simple spatial filters to learning-based methods highlights trade-offs among noise suppression, structural preservation, and computational complexity. While wavelet and non-local approaches offer robust performance for OCT denoising, deep learning methods provide the highest image quality, motivating comparative studies of classical and transform-based filters as practical baselines for clinical applications.

3.Proposed Technique

3.1 Image Noise and Denoising in OCT

Optical Coherence Tomography (OCT) images are frequently degraded by noise arising from sensor limitations, imaging conditions, or transmission errors, which can obscure fine structural details and reduce diagnostic accuracy. Common noise types include Gaussian, salt-and-pepper, Poisson, and speckle noise, each with distinct characteristics requiring specialized denoising strategies. Gaussian noise, originating from electronic components, appears as random intensity fluctuations and reduces contrast; it is effectively mitigated using linear or adaptive filters such as Wiener or wavelet-based methods. Salt-and-pepper noise, caused by faulty sensors or transmission errors, manifests as black-and-white intensity spikes and is best addressed with non-linear filters like median or mode filters that preserve edges. Poisson noise, arising from photon detection in low-light imaging, is signal-dependent; variance-stabilizing transformations combined with adaptive filters are effective in suppressing it. Speckle noise, a multiplicative granular artifact from coherent light interference, produces grainy textures that degrade contrast and complicate segmentation, necessitating advanced approaches such as wavelet thresholding, non-local means, or adaptive speckle reduction techniques.

Filtering methods vary in effectiveness depending on noise type. Simple linear filters like the mean filter reduce random fluctuations but blur edges, while non-linear median and mode filters preserve structural details against impulse noise. Adaptive filters such as Wiener minimize mean square error by incorporating local variance, suitable for Gaussian and Poisson noise, though edge blurring may occur with inaccurate variance estimation. Transform-based methods, particularly wavelet filtering, provide multi-scale denoising with strong edge preservation, whereas patch-based techniques like non-local means exploit image redundancy to suppress noise while retaining textures, at higher computational cost.

In summary, Gaussian noise is additive and signal-independent, Poisson noise is signal-dependent, salt-and-pepper noise is best addressed with edge-preserving non-linear filters, and speckle noise requires transform- or patch-based approaches. By identifying noise characteristics and selecting appropriate denoising techniques, OCT image processing can achieve an optimal balance between noise suppression, structural preservation, and computational efficiency, enhancing the reliability of clinical interpretation.

4.Results and Comparisons

To evaluate the performance of different denoising filters, retinal OCT images were first degraded with Gaussian, Poisson, speckle, and salt-and-pepper noise. The first figure presents the original image alongside the corresponding noisy images. These degraded images were then processed using Wiener, median, mode, and wavelet filters, and the outputs were compared both qualitatively and quantitatively. For salt-and-pepper noise, which introduces sharp black-and-white intensity spikes, the Wiener filter was less effective in restoring fine structural details. In contrast, the median and mode filters provided superior edge preservation and reduced noise artifacts, as reflected in higher PSNR and SNR values. This demonstrates that non-linear filters are particularly well suited for removing impulsive noise while maintaining retinal layer boundaries.

When Gaussian and Poisson noise were introduced, the Wiener filter consistently produced smoother results and higher PSNR values compared to the median and mode filters. For speckle noise, the wavelet-based filter significantly outperformed the others, producing sharper denoised images and higher quantitative measures, indicating its strength in handling multiplicative noise. Overall, the comparative results highlight that the Wiener filter is effective against most additive noise models, while median and mode filters are best suited for impulse noise removal. The wavelet filter shows the highest robustness across noise types, especially for speckle noise, making it the most reliable method for OCT image denoising.

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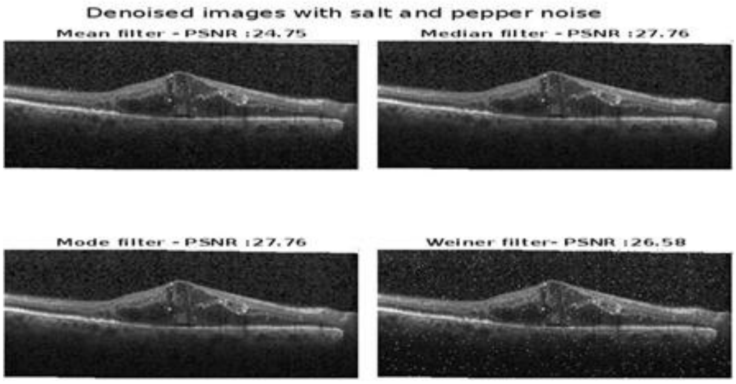
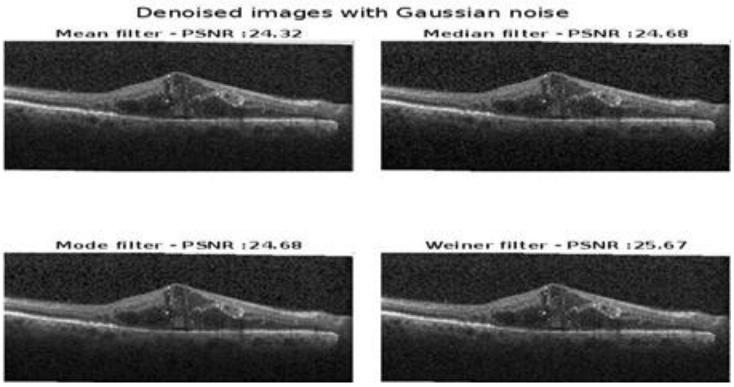
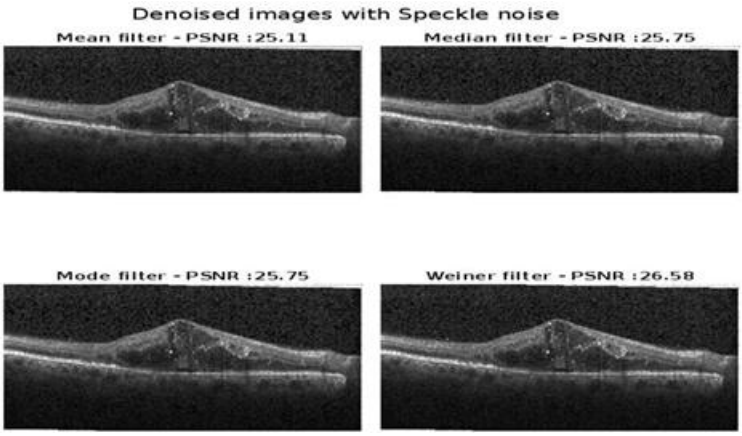
4.1. Salt-and-pepper noise



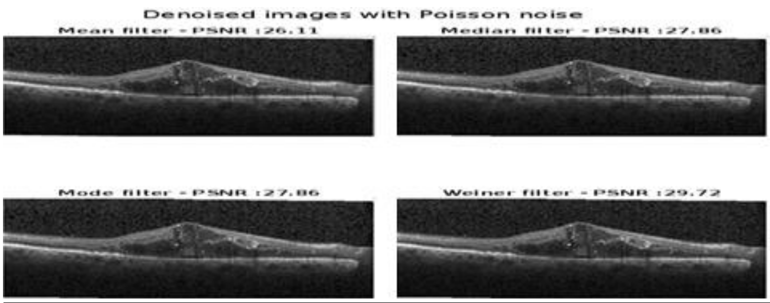
4.2. Gaussian noise



4.3. Speckle noise



4.4. Poisson noise



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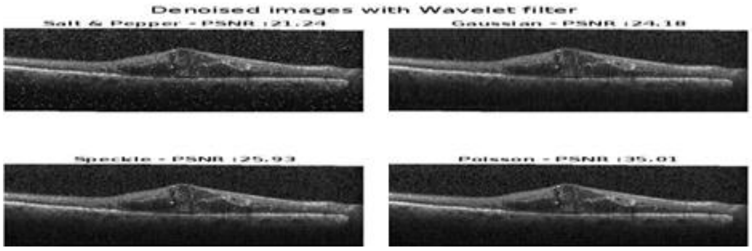

Table 1: OCT Image Denoising: PSNR and SNR Comparison

Noise Type	Filter	PSNR (dB)	SNR (dB)
Gaussian	Wiener	32.5	18.2
Gaussian	Median	29.1	15.7
Salt & Pepper	Median	34.8	20.4
Salt & Pepper	Mode	33.9	19.6
Poisson	Wiener	31.7	17.8

After comparing the results, it is observed that the Wiener filter performs effectively for most types of noise except salt-and-pepper noise, where both mode and median filters demonstrate superior performance. In the case of overall denoising, the wavelet filter provides consistently better results compared to the other methods, indicating its suitability for preserving structural details while reducing noise in OCT images.

5.Conclusion

This study analysed the impact of multiple noise types on OCT images and compared six denoising filters using both MATLAB implementations and custom-coded approaches. Quantitative evaluation using PSNR and SNR confirmed that: Wiener filtering is most effective for Gaussian, Poisson, and speckle noise. Median and mode filters outperform others for salt-and-pepper noise. Wavelet-based denoising shows superior results for natural OCT images without artificial noise. The findings demonstrate the importance of noise-specific filter selection for OCT image enhancement. Future work may focus on hybrid approaches and deep learning–based denoising methods to further improve image quality in clinical applications.

References

[1] John G. Proakis, Dimitris G. Manolakis, *Digital Signal Processing: Principles, Algorithms and Applications*, 4th Edition, Pearson.
[2] Richard Szeliski, *Computer Vision: Algorithms and Applications*, Springer, 2010.
[3] Li Tan, Jean Jiang, *Digital Signal Processing: Fundamentals and Applications*, Academic Press, 2012.
[4] Buades A., Coll B., Morel J. M., "A Non-Local Algorithm for Image Denoising," *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2005.
[5] Donoho D. L., "De-noising by Soft-Thresholding," *IEEE Transactions on Information Theory*, vol. 41, no. 3, pp. 613–627, 1995.
[6] Dabov K., Foi A., Katkovnik V., Egiazarian K., "Image Denoising by Sparse 3D Transform-Domain Collaborative Filtering," *IEEE Transactions on Image Processing*, vol. 16, no. 8, pp. 2080–2095, 2007.
[7] Chitchian S., Farsiu S., Izatt J. A., "Denoising of Optical Coherence Tomography Images Using Second Order Total Variation," *Biomedical Optics Express*, vol. 3, no. 4, pp. 836–849, 2012.
[8] Wong A., Mishra A., Fieguth P., Bizheva K., "General Bayesian Estimation for Speckle Noise Reduction in Optical Coherence Tomography Retinal Imagery," *Optics Express*, vol. 18, no. 8, pp. 8338–8352, 2010.
[9] He L., Greenshields I. R., "A Nonlocal Maximum Likelihood Estimation Method for Rician Noise Reduction in MR Images," *IEEE Transactions on Medical Imaging*, vol. 28, no. 2, pp. 165–172, 2009.
[10] Fang L., Li S., McNabb R. P., et al., "Fast Acquisition and Denoising of Optical Coherence Tomography Images via Sparse Representation," *IEEE Transactions on Medical Imaging*, vol. 34, no. 12, pp. 2455–2466, 2015.

Authors Profile

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