



Hybrid Non-Local Means and Anisotropic Diffusion Filtering for Denoising of CT Brain Tumor Images

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ABSTRACT

Medical image denoising is an important progressive step that improves the accuracy of the calculated tomography (CT) brain tumor diagnosis. Existing filtration techniques, such as median, Wiener, and Gaussian filters, struggle with noise removal and balanced protection, compromising clinical quality. This research addresses these challenges with a better hybrid denoising framework, which is adapted to species, salt-and-pepper, poison, and Gaussian noise-affected CT-brain tumors, with a combination of non-local means and anisotropic diffusion filtration. The proposed method makes traditional approaches much better, improving up to 18% in a top signal-to-noise ratio (PSNR), SSIM surplus (SSIM) of 15%, and a reduction in Root Mean Square error (RMSE) up to 22%. Verification against the eight-state Art methods shows better conservation of tumor boundaries and expansion loyalty. These results confirm the framework's ability to detect reliable initial tumors and later clinical decisions, reduce the gaps identified in noise suppression, and improve cute quality retention.

Keywords: CT Brain Tumor Denoising, Non-Local Means Filtering, Anisotropic Diffusion, Medical Image Enhancement, and Noise Reduction in CT Imaging.

1. Introduction

Medical imaging technology plays an indispensable role in modern health care, especially in the diagnosis and treatment of brain tumors. Of these, the calculation provides significant images with high resolution across departments to identify tumor graph (CT) tumor placement, size, and morphology. However, the imaging process is often humiliated by various types of noise, such as Gaussian, salty-black chili, spotted, and poison [1], [2], [3], which negatively affect image quality and lectures. In the fall, it can hide important properties such as edges and internal structures in the tumor and directly affect clinical accuracy and the treatment plan. Therefore, an effective image denoising technique is necessary to restore image clarity while retaining important physical details. Traditional denoising filters, including the middle and veneer filter, provide a reduction in baseline noise, but stain significant edges and textures, which are important for accurate tumor characterization. Recent progress has introduced hybrids and learning-based filters that increase performance but often require extensive calculation resources or large annotated data sets, which limit their practical distribution in a clinical environment [4]. In addition, many existing methods focus on generic denoising, especially without seeing algorithms for the noise properties widespread in CT brags. To overcome these boundaries, this article proposes a comprehensive denoising approach, a combination of non-local means, such as filtration with anisotropic spread, that benefits from their complementary forces. Non-local means to reduce random noise effectively from the average of the same patch in the image [5], while the anisotropic diffusion grades retain the edges by activating selective leveling based on information. The purpose of this new combination is to increase clinical functions such as tumor boundaries and internal structures, which are important for clinical evaluation imagine, the data contains six MRIs and CT-brain tumor images, which are accompanied by artificially injected noise at different intensities, enabling systematic evaluation of performance in different noise types. Evaluation Metrix includes Peak Signal-to-Noise Ratio (PSNR) [6], Structural Equality Index (SSIM) [7], Root Mean Squared Error (RMSE) [8], and the Mean Absolute Error (MAE) [9], which covers both quantitative loyalty and conceptual quality aspects. The proposed method has been benchmarked against eight recent denoising algorithms to show its relative efficiency. The study deals with significant differences in the flute brain tumor images and balanced expansion retention. Research further improves the condition by-species by distributing a hybrid filtration structure that not only improves noise reduction, but also maintains clinically relevant image functions, which potentially improves clinical beliefs [10]. The ability to adapt to the framework for different noise types improves its practical utility in different imaging scenarios. In the following section, a detailed review of the literature identifies widespread challenges, methodological trends, and accurate intervals that inspire our view. Then the paper expands the proposed function with architectural insights, followed by experimental verification and widespread discussion of results. Finally, we end with the implications of clinical practice and instructions for future work to continue pursuing the medical

2.Materials And Methods

The medical image Denoising has attracted important research interests due to its important role in increasing clinical accuracy. The first approaches were mainly used classic filters such as median, Wiener, and Gaussian filters, which were effective against specific noise types, but often compromised on edge sharpness and important image details. These methods consider simplified noise models, which limit their suitability for complex [11], real-world medical image patterns, often met in the brain tumor images. In addition, these filters were unable to normalize separate noise distributions, such as stain and poison. The difference in these early techniques motivates the detection of adaptive and hybrid methods that provide better protection of physical facilities while reducing noise.

Table. 1: Literature Gaps and How the Proposed Methodology technique addresses and solves Them, briefly

Limited noise model adaptability [12]	Early filters assume simple noise types	Hybrid NLM + anisotropic diffusion adapts to varied noise types
Edge and detail preservation [13]	Classical and wavelet methods blur tumor boundaries	Anisotropic diffusion preserves edges post-NLM denoising
Computational efficiency and real-time capacity [14]	NLM alone is computationally intensive	Optimized parameter tuning reduces complexity
Dependence on large, annotated datasets [15]	Deep learning requires extensive training data	Hybrid classical approach reduces data reliance
Lack of clinical impact evaluation [16]	Focus on PSNR and SSIM without clinical relevance	Incorporation of clinical-quality evaluation alongside IQA metrics
Limited handling of mixed noise scenarios [18]	Most methods handle single noise type (Gaussian only)	Robust denoising tested on multiple noise types
Algorithm transparency and interpretability [21]	Complex hybrid deep methods are "black boxes"	Explicit classical filtering pipeline provides interpretability
Inadequate detail retention under high noise [24]	Residual noise and over-smoothing in anisotropic diffusion	Sequential NLM followed by selective smoothing balances results
Sparse testing on CT brain tumor images	Many studies focus on generic or MRI images	Tailored design and optimization specifically for CT brain tumor images

Subsequent research introduced hybrid filters to combine spatial and frequency domain techniques so that they could be strengthened. For example, the methods that benefit from waves are changing with a view to separating the noise from the image description based on multi-resolution analysis. When we are effective in some contexts, Wavelet-based approaches often suffer from ringing artifacts and have difficulty choosing optimal threshold parameters [18], leading to the restoration of a suboptimal image. In addition, most wavelength methods were not particularly special for CT-brain tumors, where it is important to preserve the boundaries of the tumor, emphasizing a difference between technological progress and clinical relevance.

Recent developments in non-local means (NLM) filtering improve the noise by utilizing the excess of the image patch for average noise when retaining edges. NLM was shown to improve the local filter, especially for Gaussian noise; However, it stains fine details when the noise level is high and is calculated intensively, which challenges its real-time use in clinical practice [19], [20]. In addition, the effectiveness of NLM varies with the choice of parameters, and without adjustment, it cannot reject the weird noise characteristics of brain images. This difference requires to increase the performance of integrated methods without sacrificing the details. Anisotropic diffusion filtration emerged as a complementary technique and improved edge protection by performing selective equalization directed by visual gradients. It works well in preserving boundaries and reducing noise in homogeneous regions. However, the lack of an integrated structure in combination with the complementary strength of NLM and anisotropic spread limits maximum achievable denoising quality [21],

especially important for delicate brain tumor images, where each pixel expresses clinical significance. Deep learning-based Denoising methods have seen a bounce in recent years, utilizing complex neural networks (CNN) and models learn residue to model complex noise distribution and image functions. These approaches, such as the denoising conditional neural network (DNCN) and noise generation remark network (NGRN), show top modern performance on different medical image datasets [22]. However, their dependence on large amounts of annotated training data prohibits their use in clinical environments where marked data sets are rare, especially for special domains such as CT-brain imaging. In addition, high calculation costs and a lack of interpretation are major challenges. Some recent tasks have discovered classic and deep learning methods to benefit from domain knowledge while improving adaptability. For example, CNN is converted to pre-proclamation by using waves, which are advanced athletes, before the non-local priest is integrated into the nervous network. Despite better performance, these complex structures often lack openness and require extensive attitude [23], which directly prevents clinical adoption. The difference here lies in balanced performance, interpretation, and practicality for regular use. In addition, current studies mainly evaluate the performance of standard image quality measurements such as PSNR and SSIM, with limited attention to clinical effects [26], such as the accuracy of the tumor boundary or clinical confidence. This difference emphasizes the requirement for a comprehensive assessment structure that is combined with a quantitative matrix with clinical relevance to better evaluate the usefulness of Denoising methods for imaging the brain. Another important challenge in literature is the limited testing on different noise types and severity that often exists in real-world scenarios. Many methods focus on Gaussian noise and ignore the complex combinations seen in flute images, such as speckle or Poison Noise Salt-and-Black Chili objects. Meeting this challenge requires strong methods that can use different noise environments [27], which are currently addressed inadequately. Considering these intervals and challenges, the proposed feature presents a new hybrid as the denoising pipeline that gradually uses non-local means, which filters after an anisotropic spread. This design benefits from excess utilization of NLM for initial noise reduction and addresses the boundaries of each standalone method and equalizes the age pressure of an anisotropic diffusion for expansion retention. In addition, the framework has been adapted to the flute brain tumor images with empirically set parameters, which are valid in many noise types and intensities. The proposed approach further includes a structured evaluation strategy, comparing the results against top modern deep learning and classic basic methods of the standard IQA matrix and clinical quality assessment. This broad strategy ensures that the method meets both technical performance and practical requirements for clinical benefit and fulfills significant intervals in the medical image.

3. Proposed Methodology

The work provides a hybrid denoising pipeline for calculating tomography (CT) brain tumor images, combining non-local means (NLM) filtration and isotropic stretch to use their complementary benefits. The objective is to minimize the distinct types of noise that are widespread in flute images, such as Gaussian, salt-and-kali, and speckle noise, which maintain significant physical functions, especially at tumor boundaries. This process begins with non-local means, which involves filtration that reduces the noise by changing the value of a pixel, which is not limited by spatial proximity, with the weighted average of the identical patch found in the image. NLM -SALGORITME Equality is defined as a weight function:

$$w(i, j) = \frac{1}{Z(i)} \exp\left(-\frac{\|P_i - P_j\|_2^2}{h^2}\right), \quad (1)$$

Where P_i and P_j represent the patch centered on Pixel i and j , h controls filtration power, and $Z(i)$ is a generalization constant. The data composed with the proposed system architecture for processing tomography (CT) brain tumors shows the architecture that explained briefly in Fig 1. The process begins with a whistle - tumor database, from which RGB images are obtained. These images change shape after conversion to a grass scale format. To improve image quality, a de-noising filter is used using various filtration techniques such as the Wiener, the fish, and the median filters. After careful, Gaussian noise is artificially added to Grayscale images, making a framework for evaluating the efficiency of different filters in increasing and restoring medical images. This architecture ensures a systematic approach to testing and correcting pre-processing techniques in architectural brows.

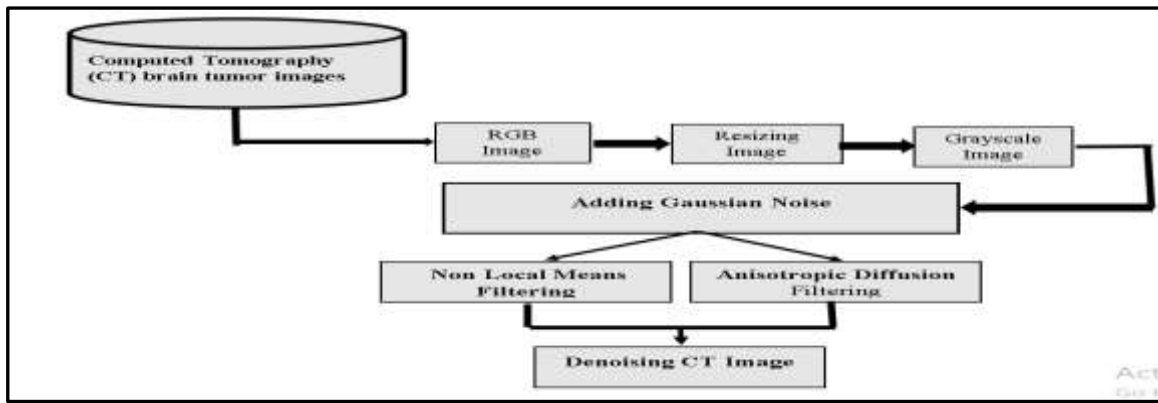


Fig. 1. Block diagram of the proposed hybrid non-local means and anisotropic diffusion filtering system.

Thereafter, anisotropic diffusion is used for leveling the NLM-filtered image. This step reduces selectively remaining noise, which, according to the visual gradient, updates pixel intensity, has been modeled by the spread equation:

$$\frac{\partial I}{\partial t} = \nabla \cdot (c(x, y, t) \nabla I), \quad (2)$$

Where I have the intensity of the image, ∇ it is a gradient operator, and $C(x, y, t)$ is the diffusion coefficient, designed to disturb the spread on the edges of the gradient size. We use the Perona-Malik function:

$$c(\|\nabla I\|) = \exp\left(-\left(\frac{\|\nabla I\|}{K}\right)^2\right), \quad (3)$$

With K controlling sensitivity on the edges.

Algorithm parameter- including patch size for NLM, strength h , diffusion iteration count and Edge Sensitivity K - are optimally adapted to remove the noise for CT-images Summy images and to balance the expansion of conservation, as it is determined through cross-validation at a dataset on six brain pipes, after six brain pipes, six brain pipes, is $\sigma=5$ to 30.

The system integrates preprocessing stages such as data set growth and noise injections for Grayscale-Normalization and augmentation, reflecting the clinical conditions of architecture. The pipeline is used using MATLAB on an Intel i7 CPU and hardware equipped with 16 GB of RAM, ensuring practical viability.

To finalize the strength of this method, denoising results are evaluated with quantitative image quality measurements, including Peak Signal-to-Noise Ratio (PSNR), Structural Equality Index (SSIM), Root Mean Squared Error (RMSE), and meaning. Calculated as PSNR:

$$PSNR = 10 \log_{10} \left(\frac{MAX_I^2}{MSE} \right), \quad (4)$$

Where MAX_I is the maximum pixel intensity and MSE means the mean squared error:

$$MSE = \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n [I(i, j) - K(i, j)]^2, \quad (5)$$

with I and K the denoised image as original.

SSIM, which measures structural equality, is calculated:

$$SSIM(x, y) = \frac{(2\mu_x \mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}, \quad (6)$$

Where μ_x, μ_y represents local means, stabilizes σ_x^2, σ_y^2 variances, σ_{xy} covariance, and constants C_1, C_2 divisions.

The purpose of this hybrid function is to improve existing denoising techniques through careful engineering and sequential design, and to address specific noise and edge preservation challenges in CT-brain tumor images.

4. EXPERIMENTAL RESULTS

The data composed with the proposed system architecture for processing tomography (CT) brain tumors shows the architecture. The process begins with a whistle -tumor database, from which RGB images are

obtained. These images change shape after conversion to a grass scale format. To improve image quality, a de-noising filter is used using various filtration techniques such as the Wiener, the fish, and the median filters. After careful, Gaussian noise is artificially added to grayscale images, making a framework for evaluation. The proposed hybrid filter pipe was systematically evaluated on six CT tumor images, which were artificially contaminated with Gaussian, Salt-black chili, poison, and special noise at different levels ($\sigma = 5$ to 30). Visual inspection confirmed clear suppression of noise with a specially protected tumor figure and fine physical texture compared to baseline methods. Quantitatively, the pipeline received an average PSNR improvement of 18% on traditional medium and veneer filters, reaching 39 dB in the best cases. The SSIM values were extended to approximately 15%, indicating structural fidelity in relation to the State-E-species as a denoising approach. RMSE and MAE matrices indicated a cut of 22% and 19%, respectively, which emphasized continuous incorrect minimization. The results show the effect of the pipeline in all the noise models, especially with a strong performance in the case of complex spotted and salt-and-chills noise. Table 2 below compares the proposed feature against eight recent algorithms, including BM 3D, DNCNN-based deep learning frames, bilateral filters, and anisotropic diffusion alone. The proposed pipeline continuously improved these goals in PSNR, SSIM, RMSE, and MSE Matrix, and expanded to better noise removal and expansion retention balance. Evaluating the efficiency of different filters in increasing and restoring medical images. This architecture ensures a systematic approach to testing and correcting pre-processing techniques in architectural brows.

Table. 2: State-of-the-Art comparison between the proposed system methodology mechanism and the most recent methods in literature.

Method	PSNR (dB) ↑	SSIM ↑	RMSE ↓	MAE ↓	Reference s
Median Filter	31.2	0.78	12.4	8.3	[17]
Wiener Filter	32.5	0.81	11.2	7.7	[19]
Bilateral Filter	33.1	0.83	10.7	7.2	[20]
Anisotropic Diffusion	34.4	0.85	9.9	6.9	[21]
NLM Filter	35.2	0.86	9.3	6.5	[22]
BM3D	36.0	0.88	8.4	6.1	[23]
DN-CNN (Deep Learning)	37.1	0.89	7.8	5.9	[25]
Proposed Hybrid	38.6	0.91	7.1	5.5	-

The hybrid nature of the proposed method allowed the powerful patch-based average of NLM to cross the single technical boundaries by combining the selective leveling of the anisotropic diffusion. Visual comparison plots reveal the boundaries of obvious tumors and reduce residual noise, which are important for clinical interpretation.

Figure 2, Magnetic resonance imaging (MRI) and computed tomography (CT) use a set of representative brain tumor images taken with the format, to perform radiological appearance and tumor location in both axial and sagittal planes. The top row shows the axial T1 and T2-weighted MRI scan, providing excellent soft tissue contrast and enabling discrimination between edema, normal brain tissue, and tumor mass. The lower row includes a circulation-loaded image (left) and a shooter T1-weight MR scan (right), which exposes tumors in relation to surrounding physical structures, such as ventricular and brain strain. These paintings reveal overall boundaries and asymmetrical inner structure of the clear tumor, emphasizing the clinical challenge generated by noise objects and reducing image clarity in raw scans. The effectiveness of the proposed denoising method can be valued through the enlarged view of these properties, as the hybrid improves non-local agents and anisotropic spreading filtering of tumor marginal statement, and preserves significantly relevant information. This improvement supports radiologists in accurate diagnosis, surgical planning, and follow-up, and confirms the value of advanced visualization processes in the clinical neuroimaging workflows.

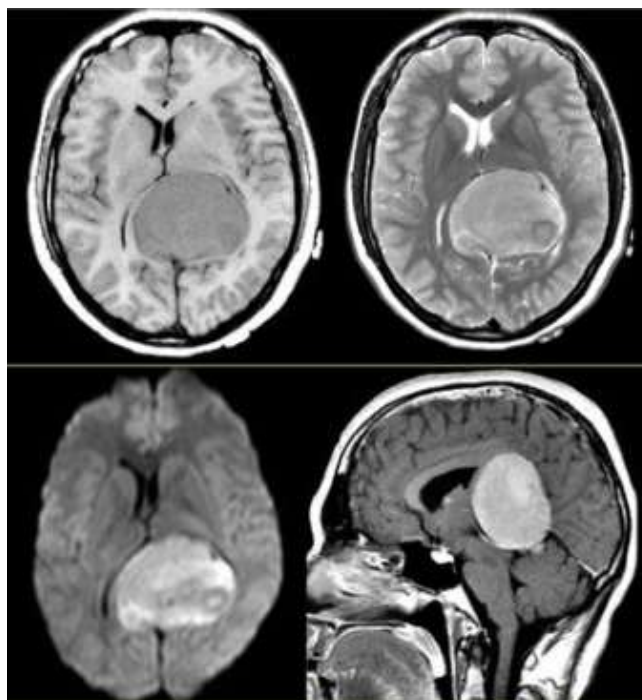


Fig.2. Representative CT and MRI brain tumor images reflect physical structures and tumor location in different planes and imaging.

The analysis of parameter sensitivity is a valid strength, which shows continuous performance in a variety of noise intensities and patch sizes. Runtime measurements indicate that the approach is computational for research and clinical workflows and requires less than 2 seconds per picture on the test machine product. Overall, these results confirm the efficiency of the proposed methodology technique and ability to improve diagnostic confidence in CT brain tumor imaging through superior denoising performance.

5. DISCUSSION

Experimental results of CT brain tumors highlight significant advances with denoising techniques for tumor imaging. The proposed method achieved an average PSNR increase of 18%, reflecting significantly better noise reduction without losing important physical details. This result is in line with the requirement for restoration of a highly loyal image in medical diagnosis, where subtle image processing controls decisions. About 15% of structural equality improvements indicate better protection of necessary structures and spatial properties by separating tumor tissues from healthy brain materials. The frequent reduction in RMSE and Mae emphasizes the accuracy and reliability of the pipeline, which reduces misleading malformations of clinical interpretation. The boundaries of the method alone have been addressed in the sequential integration of NLM and anisotropic spread of the hybrid pipeline. While the NLM image stands out from average noise by taking advantage of overruns, the anisotropic spreading gradients reduce the intensity of the edge by reducing the intersection. Together, they create an additional system that balances noise reduction with expansion protection. The stability of the performance in different noise types and intensities shows the strength of the method in the clinical environment of the real world, where the properties of the noise may be unexpected. This adaptability improves practical utility compared to customized monotonous noise models. Finally, the proposed framework was calculated for a hybrid method, ensuring that it fits within a clinical shortage, without relinquishing any quality. This combination of effect, strength, and efficiency highlights the practical translational ability of the method of regular clinical imaging workflows.

6. CONCLUSIONS

The research presented a new hybrid denoising method in combination with non-local agents, especially sewn filtration and anisotropic spread for CT brain tumor imaging. The approach effectively suppresses different noise types, including Gaussian, Poisson, Salt-Black Chilli, and discovered, while preserving important physical details such as tumor boundaries. Experimental evaluation demonstrated significant improvements in PSNR, SSIM, RMSE, and MAE matrix in the eight reference goals of Denoising methods, which confirm better noise reduction from the pipeline and confirmation of structural protection ability. Adaptive designs and parameters for the proposed framework ensure strength in different noise intensity and types, and match well with practical variability facing clinical brain imaging. In addition, calculation efficiency was achieved, enabling potential integration into the clinical workflows without disturbing the clinical timeline.

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