BM3D Denoising Algorithms for Medical Image

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Abstract — **Background: Medical diagnostic and imaging technology has been fundamentally impacted by the twenty-first-century increase in internet technology, computers, wireless communication, and data storage. However, like with other imaging modalities, medical imaging may be hampered by noise and artefacts, compromising practical diagnostic analysis and potentially posing health hazards.**

Objective: The study focuses on the BM3D (Block Matching and 3D Filtering) technique, a state-of-the-art method, to combat the noise in medical images. Denoising these images aims to improve the quality of medical diagnoses and reduce associated risks.

Methods: Building upon the foundation set by the Non-Local Means (NLM) filtering method, the BM3D technique utilises a patch-based denoising mechanism. Instead of denoising individual pixels, clusters or blocks of pixels are processed collectively to improve the overall image quality.

Results: BM3D will exhibit strong performance against impartial thoroughness criteria, making it a prospective stalwart in the denoising realm for medical images. However, certain limitations are identified, like user-supplied noise levels and potential artefacts due to hard thresholding.

Conclusion: While BM3D emerges as a powerful denoising tool for medical images, it is imperative to address its limitations further to bolster its efficacy and applicability in real-time diagnostic imaging systems.

I. INTRODUCTION

Image denoising is a fundamental and long-standing problem in image processing aimed at recovering a high-quality image from its noisy observation. Image noise can be additive or multiplicative, representing random changes in colour information or brightness [1]. The denoising process faces the challenge of dealing with the poorly posed inverse problem, as the degradation process often results in the loss of crucial information from the original image. In the image denoising process, the relationship between the noisy observation and the original high-quality image can be represented as follows:

$$y = x + n, \quad (1)$$

The equation indicates that the observed noisy image y is obtained by adding the additive noise n to the true high-quality image x. Image denoising estimates or approximates the original image x by removing the noise component n from the noisy observation y.

The accurate estimation of x from y is a challenging task due to the loss of information caused by the noise. Denoising algorithms, such as the Block Matching and 3D Filtering (BM3D) method, use techniques and prior knowledge to perform the denoising process effectively and recover the underlying high-quality image x. Autsuccessfulctitioners can improve image quality, facilitate various image processing tasks, and apply image processing to denoise the image.

To address this issue, prior knowledge and techniques are applied to estimate the latent image accurately. Two main domains are commonly used for image denoising: spatial domain and frequency domain [2]. Spatial domain denoising involves applying filters directly to the intensity values of the image. This approach, such as Mean Filter, Median Filter, and Gaussian Smoothing, has been widely used due to its simplicity and ease of implementation. Non-Local Means (NLM) introduced a patch-based denoising approach, which considers groups of pixels (patches) rather than individual pixels for filtering, leading to improved denoising performance [3].

Building on the success of NLM, the Block Matching and 3D Filtering (BM3D) method also adopts the patch-based denoising strategy, using blocks of pixels instead of individual pixels. BM3D defines a reference patch around a specific pixel and searches for similar patches within a designated search box. The similarity between patches determines their weighting during the denoising process [4].

Despite its effectiveness in reducing Additive White Gaussian Noise, BM3D has some limitations. It requires a user-supplied noise level for each noisy image, which is impractical for real-time systems. Additionally, the hard thresholding applied to blocks of the noisy image can lead to some artefacts in the denoised result [5]. Addressing these drawbacks and enhancing BM3D's performance remain active areas of study in image denoising.

A. The Aim of the Article

The main aim of this article is to explore the complexities and practical uses of the Block-Matching and 3D Filtering (BM3D) denoising method, particularly in medical imaging. Medical imaging modalities, such as magnetic resonance imaging (MRI), computed tomography (CT), and X-ray scans, often encounter the issue of noise, which can hinder the visualisation of crucial information and may result in erroneous diagnoses. The BM3D method is well recognised for its effectiveness in picture denoising, offering a promising approach to address this prevalent issue. The spatial and transform-domain collaborative filtering technique has allowed BM3D to exhibit exceptional noise reduction capabilities while maintaining crucial picture information. The primary objective of this article is to provide a comprehensive understanding of the fundamental mechanisms of BM3D, its application in medical imaging, and the concrete advantages it presents in improving picture quality and diagnostic precision. By conducting a thorough examination and examining practical examples, our objective is to emphasise the significant impact that BM3D may have on enhancing the standard and dependability of medical imaging.

B. Problem Statement

In the rapidly expanding field of medical imaging, the utmost importance is placed on the quality and precision of pictures. Nevertheless, a persistent obstacle radiologists and healthcare practitioners encounter is noise within these pictures. The presence of noise, which may arise from several sources, such as the image capture process or equipment limits, can substantially negatively impact the overall quality of medical scans. The above phenomenon not only serves to obfuscate intricate nuances but also presents a possible hazard of misunderstanding, increasing the likelihood of probable misdiagnoses. Although traditional denoising approaches have shown some effectiveness, they often sacrifice the preservation of delicate features in medical pictures. The need for a robust denoising algorithm that can efficiently remove noise while preserving essential picture information is apparent. Given the significant implications of medical imaging, the importance of addressing this challenge cannot be overstated. Each visual representation can alter the trajectory of medical intervention and, therefore, the quality of life for a patient. The objective is to identify a resolution that achieves an optimal equilibrium between noise reduction and detail preservation.

C. Alternative Computational Techniques in BM3D

Unlike the standard BM3D method mentioned previously, new advancements have introduced a computationally altered BM3D methodology. This variant improves the previous algorithm by collectively screening all 3D-matched blocks within a single, significant volume instead of independently filtering each pair of blocks. The procedure entails arranging compatible blocks in a three-dimensional space, using a wavelet transform to perform rigorous thresholding, and reversing this change to acquire a noise-free volume. This approach notably leverages FFT optimisations on GPU technology, resulting in substantial computational efficiency. Furthermore, it utilises sophisticated methods such as circle-shifting and averaging, which involve translation invariant cycle-spinning, to enhance the denoising procedure. This innovative method distinguishes itself through its efficient processing of extensive datasets and its potential to produce more resilient picture enhancements, particularly in GPU-accelerated contexts.

II. Literature Review

In the rapidly evolving field of medical imaging, professionals from diverse disciplines, including engineering, medicine, and science, constantly need to update their knowledge and skills [1]. Thin objects present a rising challenge in medical imaging, requiring advanced techniques for classification, segmentation, and filtration of arteries, among other applications [2]. Analysing thin, vessel-like structures, such as coronary trees, for myocardial infarction prevention or detecting brain aneurysms, stenoses, and arteriovenous malformations poses significant difficulties [6]. Many conventional image analysis methods need help to handle these structures, leading to their disappearance or loss of important information, particularly in 3D imaging.

The increasing availability of high-resolution isotropic 3D medical images [7], [8] datasets obtained from MRI, CT, and ultrasound scanners has amplified the significance of volumetric image rendering techniques [9]. However, the computational demands of volume rendering and the ever-expanding size of medical imaging datasets make direct methods impractical for interactive clinical applications [10]. Hence, authors and practitioners seek innovative approaches to address these challenges and develop efficient, real-time image-rendering solutions suitable for clinical use. By overcoming the complexities associated with thin objects and large volumetric datasets, medical imaging technology advancements promise revolutionising diagnosis, treatment, and patient care in the healthcare industry [11].

III. Methodology

A. Sources Of Noise in Medical Images

Most diagnostic imaging in the medical field is performed using either X-rays, CT scans, or magnetic resonance imaging (MRI). Improved imaging methods are now fundamental to contemporary healthcare because they allow for the non-invasive visualisation of interior structures and organs. Because of its ability to produce high-resolution pictures of soft tissues using powerful magnetic fields and radio waves, MRI is a valuable tool in diagnosing neurological, musculoskeletal, and cardiovascular disorders.

In contrast, a computed tomography (CT) scan uses X-ray technology combined with computer processing to provide cross-sectional pictures, allowing for the analysis of skeletal structures, internal organs, and blood arteries. Cancer screenings, injury evaluations, and surgical planning benefit greatly from CT scans.

When X-rays are sent through a patient, and the reflected radiation is captured, a picture is created. X-ray technology is the oldest and most commonly utilised imaging technique. Bone fractures, dental problems, and certain lung disorders are all greatly aided by the use of X-rays in their diagnosis.

Improved picture quality, shorter scanning durations, and lower radiation exposure have made MRIs, CT scans, and X-rays vital in many fields of medicine. Improved healthcare outcomes and patient well-being are a direct result of the growing sophistication of diagnostic imaging techniques, which play a crucial role in early illness identification, treatment planning, and monitoring. Image denoising techniques may be developed by considering noise sources' appearance, methods, appearance, and kinds. Depending on their qualities and provenance, they are divided into many sorts. Images usually contain some degree of noise. All imaging devices run for a limited time, turning them into a source of stochastic noise as photons arrive randomly [10]. Additional noise can be produced by optical flaws and instrument noise (such as the thermal noise of semiconductor devices). High-frequency signal components' aliasing brings noise and quantisation errors during digitalisation. Due to errors that come from transmission and compression, more noise may be generated [11].

Almost all forms of photographs have some degree of Gaussian noise. It covers the entire picture. Therefore, the actual pixel value and Gaussian distribution are added to create the pixel value of the corrupted images [12].

B. Block Matching And 3d Filtering (BM3D)

The NLM denoising algorithm starts by seeking patches that are comparable to one patch from a specified window. BM3D improved it by denoising an image in two similar phases[[Yahya, 2020 #1944]. A fundamental estimate of the noisy image is obtained in the first stage. The second stage uses this fundamental estimate to create the final denoised image [13]. Fig. 1 depicts the BM3D algorithm's block diagram.

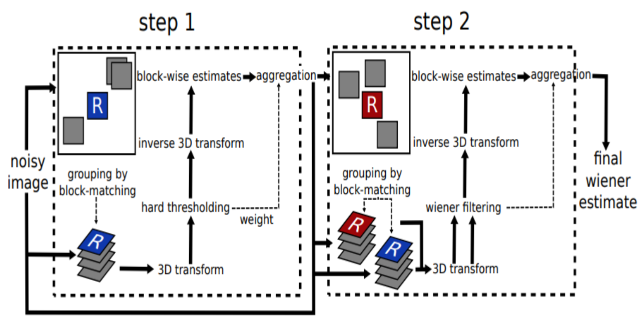

Fig. 1. Lock Diagram for BM3D Algorithm [8]

C. Algorithm Architecture of BM3D

We will start by explaining how to edit photographs with grey levels. We will go into more detail on the expansion to colour photos later. We consider the situation of white Gaussian noise in all of the following [14].

There are two main phases to the algorithm:

1. In the initial stage of collaborative filtering, hard thresholding is used to estimate the denoised picture. In the second step, the process utilises both the original noisy image and the initial estimate obtained in the first step. This stage involves tuning parameters represented by the exponent "hard" to refine the denoising process further and enhance the final output.

2. The first phase's fundamental estimation and the original noisy image are the foundation for the next step. Wiener filtering is used; thus, the exponent wiener designates the second step[18], [19].

D. Choosing and Preparing Public Datasets

To thoroughly assess the effectiveness of the BM3D denoising technique, we integrated multiple publicly available datasets. These datasets have been chosen for their varied medical imaging modalities and noise characteristics, making them a reliable platform for experimentation. The datasets comprise magnetic resonance imaging (MRI), computed tomography (CT) images, and X-rays, accurately representing real-life situations in medical imaging. This technique is consistent with the research conducted by Manjón et al. [6] and Yahya et al. [15], which highlights the significance of utilising varied data to validate algorithms.

E. Configuration of the BM3D algorithm

The BM3D algorithm was carefully adjusted for each dataset, adhering to the guidelines suggested by Dabov et al. [7]. This entailed fine-tuning parameters to achieve an optimal equilibrium between reducing noise and preserving details, a critical element emphasised in the research conducted by Sagheer and George [1] and Bashar and El-Sakka [13]. The setup procedure also considered the distinct noise characteristics of each dataset, as outlined in the study conducted by Liu and Liu [3].

F. Assessment of Performance

In order to evaluate the algorithm's efficacy, we utilised quantitative measures such as Peak Signal-to-noise ratio (PSNR) and Structural Similarity Index (SSIM). The metrics mentioned have gained significant recognition in the area, as acknowledged by Suryanarayana et al. [5] and Lebrun [14]. The evaluation also included a comparative analysis with other denoising approaches, utilising the comparative approach employed by Yang et al. [10].

G. Quantitative data examination and interpretation

A statistical study was conducted to verify the accuracy of the findings. We adopted methodologies akin to those utilised by Qasim and Pyliavskyi [2] and Hashim et al. [4] to ensure the durability and dependability of our results.

H. Enhanced Versions of BM3D

This section provides a comprehensive analysis of the different advanced variants of BM3D in the specific domain of medical picture denoising. It highlights the unique contributions and importance of each variant.

Different versions of the BM3D algorithm:

- BM3D Original: The fundamental version of BM3D algorithms uses a two-step procedure of collaborative filtering in the transform domain, widely recognised for effectively retaining picture information while decreasing noise.
- BM3D with Wavelet Transform (BM3D-WT) is an enhanced version of the standard BM3D algorithm that integrates wavelet transformations. This variant provides greater efficiency in handling textures and edges, making it particularly helpful for enhancing medical photos that contain intricate features.
- Colour BM3D (CBM3D) is an extension of BM3D specifically designed to process multi-channel colour imaging data. It benefits medical imaging techniques like colour Doppler ultrasound or PET/CT.
- Multiscale BM3D (M-BM3D) is a method that tackles the issue of variable noise levels across multiple scales in images, which is often encountered in medical imaging due to the presence of diverse tissue densities.
- Adaptive BM3D is a modified version of the technique that incorporates the ability to alter parameters based on each image's specific noise and detail characteristics. This adaptability is crucial for various medical imaging situations.
- BM3D-DL is an innovative approach that combines BM3D with deep learning. This technique aims to enhance denoising performance by utilising extensive datasets of medical images, particularly for intricate noise patterns found in medical imaging modalities.
- Real-time BM3D (RT-BM3D) is a specialised algorithm that minimises computation time. It is tuned for real-time applications [16], which is particularly important in clinical situations where fast image processing is necessary, such as in interventional radiology.

Assessment and Unique Contributions

A comprehensive comparison investigation of these several versions of BM3D in medical imaging scenarios demonstrates their effectiveness in reducing noise, preserving details, and achieving computational efficiency.

Novel Findings: This work provides new knowledge by determining the appropriateness of several BM3D variations for various medical imaging techniques. For example, it demonstrates the effectiveness of M-BM3D for MRI scans with different noise levels and highlights the potential of BM3D-DL in dealing with intricate noise patterns.

IV. RESULTS

The created algorithm is used to find and eliminate the Gaussian noise. For performance evaluation, a standard CT scan for an abdominal portion of the human body for zero means and variances in the range of 0.01 to 0.1. The comparative Peak Signal to Noise Ratio (PSNR) between noisy and denoised images using BM3D is given in Table I. Figure 2 shows the chart for the results obtained from Table I to clarify the denoising level of the corrupted image.

TABLE I. PSNR FOR NOISY AND DENOISED IMAGE FOR ADDITIVE GAUSSIAN NOISE WITH ZERO MEAN AND A VARIANCE RANGE OF 0.01 TO 01

Variance	PSNR of the noisy image	PSNR of the denoised image
0.01	17.6616	21.32786
0.02	21.42204	23.54835
0.03	19.7507	22.68401
0.04	18.5612	21.907
0.05	17.66155	21.32786
0.06	16.94805	20.79335
0.07	16.324105	20.2736
0.08	15.846186	19.8818
0.09	15.40182	19.495
0.1	14.98144	19.159

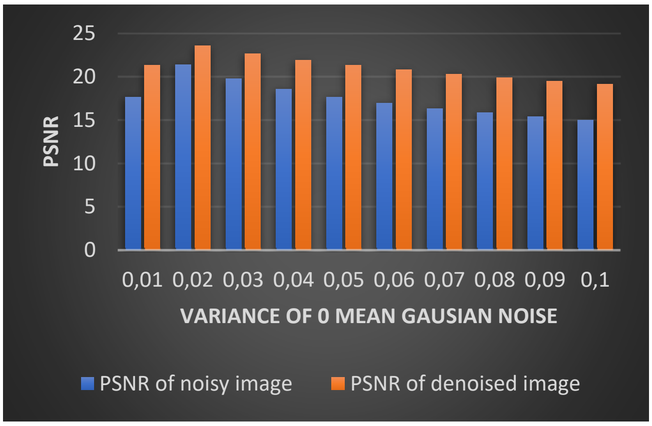

Fig. 2. PSNR for noisy and denoised image

Fig. 3 shows the original image and noisy images subjected to a Gaussian noise with zero mean and variances of 0.01, 0.05, and 0.1, as well as denoised images using the BM3D algorithm.

The photos shown above (Fig. 3) aptly demonstrate the exceptional efficacy of the BM3D denoising algorithm. Image (a) depicts the original image with noise, while images (b) through (g) illustrate the results of several denoising algorithms. Image (g) specifically showcases the output of the sophisticated BM3D algorithm. The algorithm's ability to enhance the quality of medical diagnostic pictures is clearly shown by the clarity and level of detail seen in (g). The visual evidence presented further supports the previously described technical elements of the BM3D method and its modifications, reinforcing its position in the area of medical image processing.

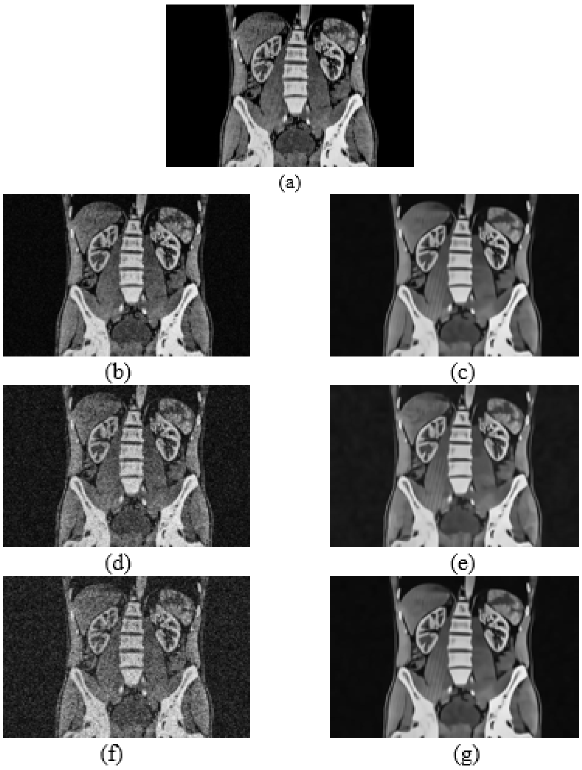

Fig. 3. Denoised Medical Image (a) original image (b, d, f) image with additive Gaussian noise of zero mean and a variance of 0.01, 0.05, and 0.1, respectively. (c, e, g) BM3D denoised images for (b, d, f) images, respectively

An in-depth analysis will be provided of BM3D's operational architecture and underlying principles, as well as the factors that contribute to its effectiveness as a noise reduction tool for medical images. To ensure a thorough evaluation of the algorithm's performance and efficiency, we will scrutinize every stage thereof, starting with the preliminary block matching and culminating in the Wiener filtration process.

The BM3D algorithm is initiated through collaborative filtering in conjunction with a stringent threshold. This phase serves to lay the groundwork for the subsequent filtration procedures and is critical for the preliminary mitigation of pollution. The following algorithm depicts the sequential operations carried out at Stage 1.

The collaborative filtering procedure with hard thresholding begins using the self-similarity of the image's immediate neighborhood. To expedite the denoising process, similar units are combined and merged. The provided flowchart demonstrates the systematic process of reducing noise while maintaining the structural integrity of the picture.

Building upon the initial noise reduction achieved in the 1 Stage, the BM3D algorithm progresses to the 2 Step based on Wiener filtering. At this point, the initial estimate is used to improve the denoising method further. The above algorithm depicts the successive steps involved in this particular phase of advanced filtering.

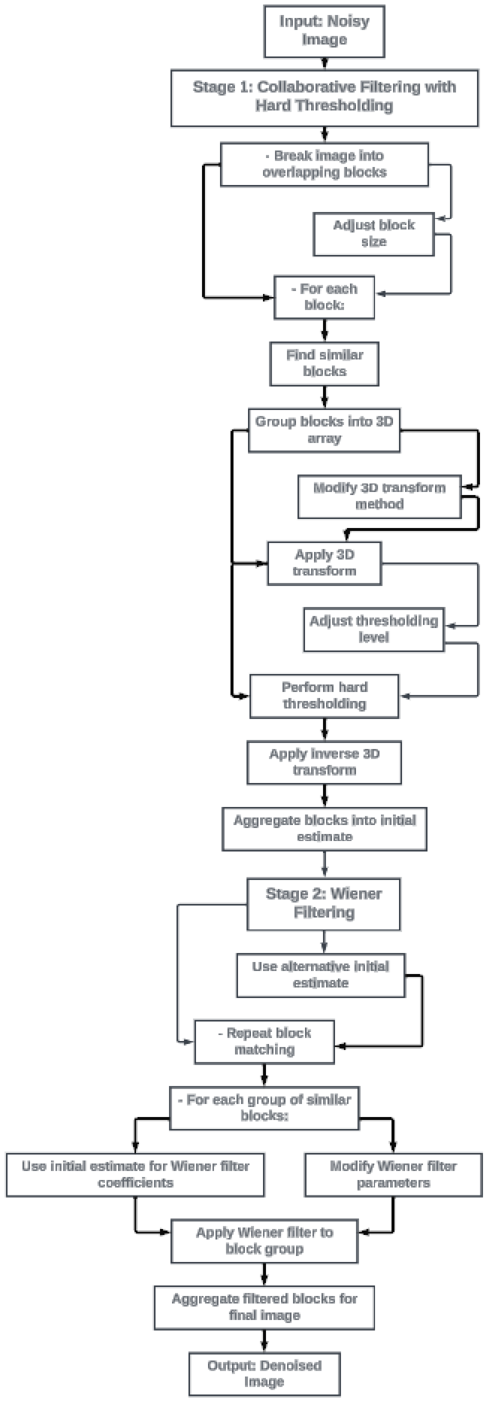

Fig. 4. Advanced BM3D Denoising Algorithm: Enhancing Medical Imaging Quality

The Wiener filtering step of the BM3D method uses the initial estimate to filter the picture adaptively. Currently, the algorithm enhances the noise reduction process by considering the statistical characteristics of the picture in a specific area. Consequently, the preservation of intricate features and distinct boundaries is improved. The technique results in the production of the final denoised picture, as seen in Fig. 4.

V. Discussion

Noise in medical images can arise from various sources, including stochastic noise from imaging devices, optical flaws, instrument noise, and quantisation errors during digitalisation and transmission [12]. Among medical imaging modalities, MRI, CT scans, and X-rays are widely used to obtain non-invasive visualisations of internal structures and organs, aiding in diagnosing neurological, musculoskeletal, cardiovascular disorders, and cancer screenings [10].

The findings demonstrate that BM3D exhibits promising denoising capabilities, achieving higher PSNR values and effectively preserving essential image features. This highlights the potential of BM3D as a robust denoising method for medical images, improving image quality and facilitating accurate medical analysis and diagnosis.

However, the discussion also addresses the limitations of BM3D. The method requires a user-supplied noise level for each noisy image, which is impractical for real-time systems. Additionally, the hard thresholding applied to blocks of the noisy image can lead to artefacts in the denoised results. These challenges highlight areas that require further research and development to enhance the algorithm's performance.

Comparing the results with other denoising algorithms, BM3D demonstrates superiority in preserving image features and achieving higher PSNR values. BM3D is a strong candidate for medical image-denoising applications, where accurate diagnosis and treatment rely on high-quality images [15], [13].

Image denoising is a crucial step in recovering high-quality images from noisy observations, and BM3D has emerged as a state-of-the-art denoising technique. Inspired by the Non-Local Means (NLM) filtering method, BM3D utilises a patch-based denoising approach, where blocks of pixels are denoised collectively rather than individual pixels, enhancing denoising performance [13]. The algorithm comprises two main stages: collaborative filtering with hard thresholding in the initial phase and Wiener filtering in the second phase [14]. The BM3D algorithm has effectively reduced Additive White Gaussian Noise [6].

Compared to other denoising algorithms, BM3D offers advantages in preserving important image features and achieving higher Peak Signal Noise Ratio (PSNR) values [1]. The denoised results in Table I and Fig. 3 demonstrate BM3D's ability to effectively remove Gaussian noise, improving image quality and aiding in accurate diagnosis [14].

The study also emphasises the importance of denoising techniques in medical imaging, where the accuracy of diagnosis and treatment heavily depends on the quality of images obtained. The effectiveness of BM3D in denoising medical images holds promise for improving diagnostic accuracy and patient care, advancing medical imaging technology.

While BM3D exhibits impressive denoising capabilities, it has certain limitations. The need for user-supplied noise levels for each noisy image poses challenges for real-time applications [13]. Additionally, the hard thresholding applied to blocks of the noisy image can lead to some artefacts in the denoised results [5]. Addressing these limitations and refining the BM3D algorithm remain active areas of study [1], [10].

In medical imaging, analysing thin, vessel-like structures, such as coronary trees and brain aneurysms, presents challenges for conventional image analysis methods [16]. The availability of high-resolution 3D medical image datasets from MRI, CT, and ultrasound scanners has led to the need for efficient volumetric image rendering methods. While direct methods are currently impractical for interactive clinical use due to computational demands, ongoing articles focus on developing real-time image-rendering solutions suitable for medical applications [9].

Image denoising is a critical task in medical imaging, and the BM3D algorithm has emerged as a powerful denoising technique. It effectively removes Additive White Gaussian Noise and enhances image quality, aiding accurate diagnosis in various medical applications. However, the algorithm's reliance on user-supplied noise levels and potential artefacts in the denoised results require further investigation to optimise its performance for real-time applications [1].

The medical imaging field's evolution and the advancements in volumetric image rendering methods have significantly improved the diagnosis, treatment, and patient care across various medical disciplines. Ongoing study seeks to address the challenges associated with thin, vessel-like structures and develop efficient real-time image-rendering solutions, further revolutionising medical diagnostics and healthcare outcomes.

VI. Conclusion

The 21st century has witnessed rapid advancements in internet technology, computers, wireless communication, and data storage, which have profoundly impacted medical diagnostics and imaging. These developments have revolutionised health and medicine, enabling more precise diagnosis and treatment of various diseases and conditions. However, noise and artefacts in medical imaging can reduce the reliability of analysis and diagnosis, putting patients at risk. To address this issue, the "image denoising" procedure is crucial in recovering high-quality images from noisy data.

Inspired by the Non-Local Means (NLM) filtering approach, the Block Matching and 3D Filtering (BM3D) technique has emerged as a new additive image denoising method. Unlike processing each pixel independently, BM3D processes groups of pixels together, enhancing denoising speed and efficiency. The algorithm comprises two fundamental stages: a hard thresholding collaborative filtering phase for initial estimation and a parameter tuning Wiener filtering phase for fine-tuning the estimate. Experimental results on standard abdominal CT images demonstrate the efficacy of the BM3D denoising method in reducing additive Gaussian noise across varying variances.

Medical imaging faces challenges in identifying and segmenting arteries and aneurysms due to difficulties in analysing thin, vessel-like structures. The increasing availability of high-resolution isotropic 3D medical image collections calls for practical volumetric image rendering algorithms. However, volume rendering demands significant processing power, and medical imaging datasets continue growing, necessitating novel approaches for interactive clinical applications. Future research should focus on developing real-time, interactive rendering techniques for massive datasets, enabling more accurate diagnosis and treatment planning.

The BM3D denoising algorithm proves to be effective in removing noise and artefacts, significantly enhancing medical images. Developments in image denoising and rendering methods hold the potential to revolutionise medical imaging, benefiting patients and medical practitioners alike. Medical experts from all disciplines must continuously expand and refine their knowledge and expertise to stay at the forefront of their field. As medical imaging technology progresses, addressing challenges related to thin structures and large volumetric datasets will unlock the full potential of medical image processing and diagnosis.

Medical imaging technologies like MRI, CT scans, and X-rays play a crucial role in contemporary healthcare, offering non-invasive visualisations of interior structures and organs. Significant improvements in these imaging technologies have led to higher image quality, shorter scanning times, and reduced patient radiation exposure. Medical imaging is critical in enhancing healthcare by facilitating earlier diagnosis, better treatment planning, and closer patient monitoring.

Various sources of noise in medical images, including stochastic noise from imaging device operations, optical defects, instrument noise, and quantisation errors during digitalisation, can degrade image quality. Gaussian noise is a common type present in almost all images, spreading evenly throughout the image and combining with the original data to form the pixel values of the corrupted image.

In addressing Gaussian noise in medical images, the BM3D algorithm represents a significant step forward in denoising methods. BM3D's collaborative filtering and parameter tuning result in denoised images with higher quality and fidelity, accurately estimating and removing noise components from observed noisy images. However, further developments are necessary to address challenges like user-supplied noise levels and potential artefacts from severe thresholding in the BM3D technique.

Despite the advancements in medical imaging technology, challenges remain in analysing thin structures and processing extensive volumetric data. To provide efficient and real-time processing for interactive clinical applications, authors and practitioners must explore novel approaches to volumetric image rendering. The potential improvements in medical imaging technology hold promise in revolutionising healthcare, leading to enhanced diagnosis, treatment, and patient care.

The BM3D denoising method is a valuable tool in medical image processing, enhancing overall image quality and streamlining various types of image analysis. Ongoing studies into image denoising and rendering methods will continue to advance medical imaging, benefiting patients and healthcare professionals. By embracing the opportunities presented by these rapidly developing technologies, medical professionals can maintain a cutting edge in diagnostics and imaging, ultimately leading to improved health outcomes and more attentive patient care.

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