Denoising Technique for CT Images

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Denoising computed tomography (CT) medical images is crucial in preserving information and restoring images contaminated with noise. Standard filters have extensively been used for noise removal and fine details' preservation. During the transmission of medical images, noise degrades the visibility of anatomical structures and subtle abnormalities, making it difficult for radiologists to accurately diagnose and interpret medical conditions.

Keywords: image denoising ; CT images ; computed tomography (CT) ; medical images

1. Introduction

Computed tomography (CT) is a widely used medical imaging modality that precisely identifies anatomical structures and abnormalities [1]. Medical imaging has revolutionized the healthcare sector by assisting medical professionals in several ways, such as in disease diagnosis, treatment, and risk prediction [2]. However, popular medical imaging modalities, such as magnetic resonance imaging (MRI), ultrasound (US) images, positron emission tomography (PET), and computed tomography (CT) images [2], are degraded by various kinds of noise, not limited to Gaussian noise, speckle noise, Poisson noise, and salt and pepper noise, which severely affects fine details of an image, such as edges, lines, and points [3][4]. For instance, positron emission tomography (PET) is a procedure that involves nuclear imaging to provide information about the operation of different tissues and organs. These images are usually degraded by a low signal-to-noise ratio and blurred edges caused by Poisson and Gaussian noise. Similarly, CT medical images are corrupted by Gaussian and salt and pepper noise, among others. Gaussian blur noise in CT imaging is caused by electronic noise, image post-processing, the reconstruction process, and quantization [5].

Ultrasound is a medical imaging modality that uses high-frequency sound waves to create real-time images of the inside of the body. It is a non-invasive and safe imaging technique widely used for diagnostic and monitoring purposes. When ultrasound waves propagate through a biological medium, the images are contaminated with speckle noise, obfuscating the pertinent details and reducing the contrast of the soft tissues, thereby degrading their overall visual quality [6]. Medical image analysis encompasses various image types characterized by their generation and appearance, and each is affected by distinct noise that deteriorates their image quality.

The major challenge in the process of medical imaging is to obtain an image without loss of any meaningful information for decision-making. Noise or artifacts corrupt the images obtained during the acquisition and further processing stages [7]. Unlike natural images, most medical images pose signal-dependent noises; hence, it is hard to remove them by using conventional raw image denoising techniques [8]. Noise refers to the random variations of brightness and color that are not part of the original image, which deteriorates the image quality and even makes them diagnostically unusable [9]. The blurry and corrupt image quality reduces the visibility of structural details and discourages further decision-making, leading to poor diagnosis, analysis, and treatment [10].

Gaussian noise is the type of noise that arises from sensor noise, heat propagation, or circuit noise that affects CT scan images. Gaussian noise introduces random fluctuations in pixel intensity levels across the image, leading to a loss of image clarity, sharpness, and fine details' preservation and restoration [11].

When CT scan images are acquired, factors such as photon statistics, electronic noise, and patient motion can introduce noise into the images [12]. The noise can obscure fine details and reduce the overall image quality, leading to information loss [13]. The main aim of image denoising is to remove the noise while preserving the details of the image and cover aspects such as edge preservation and robustness to any artifacts [14]. In addition, denoising and enhancement of medical images can be helpful in image restoration, feature extraction, and in reducing distortion of images obtained from complex imaging modalities such as MRI, PET, and CT [15][16]. Several noise reduction approaches have been reported to address this problem during preprocessing and post-processing stages. These approaches include Gaussian filters (GF), mean filters (mean-F), median filters (Median-F), bilateral filters (BF), wiener filters (WF), non-local mean filters (NLM), and denoising convolutional neural networks (DnCNN) [17][18][19][20]. However, these conventional spatial filtering techniques [17][18][19][20][21] for image denoising are still faced with the challenge of preservation of image details, which causes the blurring effect, handling of complex noise patterns, parameter tuning, artifacts, and computational complexity, which affect their direct use for medical diagnostic purposes [20][21]. For instance, Vimala [22] proposed a dual-tree DWT combined with wiener filters, used for an image affected by white Gaussian noise, proving that DT-DWT and wiener filters effectively denoise white Gaussian noise. However, the estimation of sub-optimal characteristics led to sub-optimal denoising results. Zhang et al. [23] proposed a non-local (NL) means filtering scheme for Gaussian noise removal, where the resemblance of local patches determines the pixel weights. When the window size of the image is reduced to only a one-pixel value, the NL-means filtering becomes the same as the bilateral filter [24].

It is demonstrated that the significant challenges faced by filters in [17][18][19][20][21][22][23][24][25][26][27][28][29][30][31] were edge preservation, image restoration, computational intensity, and the blurring effect problem, which decreases image sharpness, obstructs the view of the underlying anatomy, and renders the CT scan images unsuitable. In recent years, several convolutional neural network (CNN)-based methods have been proposed for natural image denoising, and the application of a three-layer CNN for low-dose CT has shown promising results. Using a deep-CNN improves the image processing performance because of its strong symbolic power. However, when trained with a widely used pixel-level loss function, the CNN-based models often suffer from vanishing gradients by introducing blurring in denoising images [32]. Additionally, striking a balance between noise reduction and retention of clinically relevant information remains a challenge. Therefore, a wavelet-based image deblurring and restoration ensemble approach is proposed to enhance image quality, preserve edge information, and improve image restoration while eliminating the entire image noise.

The proposed ensemble approach uses the denoising capabilities of an anisotropic Gaussian filter (AGF), wavelet transform, and denoising convolutional neural network (DnCNN). The AGF is used as a preprocessing operation to reduce Gaussian noise in the image by selectively smoothing the image while preserving the edges and fine details, effectively reducing noise levels. When applied with suitable parameters, it helps reduce blurring effects in the image and restore sharpness. The Haar transform wavelet is a preprocessing operation known for preserving edges due to its ability to capture sharp transitions in the image. An inverse Haar transform is performed to reconstruct the enhanced image. The denoising CNN is trained on pairs of degraded images (blurred and noisy) and their corresponding clean, sharp versions. The CNN learns to map the degraded images to their clean counterparts, effectively removing the blurring effect and restoring the image. Both AGF and Haar transform inherently contribute to edge preservation, considering that the AGF preserves edges while selectively smoothing other regions, and the Haar transform allows for directional analysis, which can further enhance the edge preservation during the restoration process with the DnCNN. Anisotropic Gaussian filters adaptively adjust their parameters based on local image features, allowing for effective noise reduction without sacrificing important image details.

2. Image Denoising Technique for CT Images

Noise in medical images refers to unwanted random variations or distortions superimposed on the underlying image information. It degrades the quality and clarity of images, making it challenging to accurately interpret and analyze them [33]. Noise can arise from various medical imaging sources, including imaging equipment, signal acquisition, patient factors, and image processing [34]. Image denoising aims to obtain the best of an original image from the corrupted image. Noise reduction improves the perception of images and usually results in better performance for different image analysis and computer vision algorithms [35]. In [36], the authors pointed out that during the transmission of medical images, noise becomes a dominant factor that deteriorates and degrades the image's contrast, reducing its quality and appearance and creating problems in the diagnostic phase. Salt and pepper noise (SPN) and Gaussian noise (GN) are common types of noise in medical images that occur in acquisition or data transmission through any network or medium [37][38][39]. Usui et al. [40], in their quantitative evaluation of deep convolutional neural network-based image denoising for low-dose computed tomography, eliminated Gaussian noise, and maintained sharpness using DnCNN.

In [41], Gaussian noise was added with a standard deviation of 0.002 to thoracic CT images. A fast, non-local means (FNLM) denoising algorithm removed blurring in the images. The FNLM was more efficient than conventional denoising filters, such as Gaussian, wiener, and median filters. Sarita et al. [42] assessed denoising filters for brain MRI-weighted contrast-enhanced images. The PSNR, SSIM, and MSE are statistical parameters used for analyzing the performance of the filters. The study showed that the wiener filter is considered the most efficient for Gaussian noise. In the case of speckle noise, anisotropic filters work better on low noise density, whereas the Gaussian filter works better for high noise density. Wang et al. [43] used adaptive wavelet transform and CNN for image denoising, and PSNR was calculated as high and MSE as low. In addressing Gaussian and Rician noise issues of data loss due to compression and preservation of edge details, Juneja et al. [44] used Bayesian shrinkage-based fused wavelet transform (BSbFWT) and the block-based autoencoder network (BBAuto-Net) to remove noise from MRI. A novel algorithm that combines the bilateral filter and its method of noise thresholding, using dual-tree complex wavelet transform to remove Gaussian noise in the image, was proposed by Majeetah et al. [45]. The experimental results show that the proposed algorithm is superior to other existing filtering algorithms in terms of visual quality and has very good PSNR, SSIM, and UIQI values. However, the issues around image blurring, contrast reduction, and quantitative inaccuracies of PSNR and SSIM were not adequately addressed.

The CNN and bilateral filters were used to remove Gaussian noise from CT images in [46], and the authors of [47] presented a novel window-based method to remove high-density salt and pepper noise for optimal ROI (region of interest) detection of the brain MRI images. The output was used in watermarking and extracting hidden data in this type of image. An impulse noise removal algorithm model was proposed based on logarithmic images before medical images [48]. Experimental results using PSNR and MSE showed that the method was superior in terms of the effectiveness of impulse noise (salt and pepper noise) removal for medical images, CT, or MRI [49]. In [50], they developed a fast method based on Fuzzy Logic for Gaussian impulsive noise reduction in CT medical images. By applying parallel computing strategies, the obtained computing times indicated that the introduced filter reduced Gaussian–impulse-mixed noise on CT medical images in real time. In [51], the authors discussed how Gaussian filters effectively removed random additive noise, such as Gaussian noise that follows a uniform Gaussian distribution. However, they did not perform well in the presence of other types of noise, such as impulse noise, which caused blurring around edges and introduced halo-like artifacts in the denoised image [52]. The blurring and halo artifacts can distort the fine details of objects and degrade the overall visual quality of the image.

Gaussian noise often distorts digital images, which is an essential problem in image processing. In [53], the impulse and Gaussian noise in the CT image were removed based on the edge-preserving median filter algorithm. The sparse, non-local regularization algorithm weighted coding was used to remove the impulse and Gaussian noise in the mixed noise, and the peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) were calculated to evaluate the quality of the denoised CT image. The performance of the median filter for Gaussian noise removal could have been more effective due to its discrete nature, acceptable detail loss, and edge preservation. Authors in [23][24][25][26][27][41][42][43][44][45][46][47][48][49][50][51][52][53] discussed the challenges of image denoising based on the state-of-the-art medical image denoising techniques, such as bioinspired optimization-based filters and spatial filters using CNN, which included the preservation of image details, trade-off between noise removal and detail preservation, noise characteristics, computational complexity, and spatial and temporal coherence. However, these conventional image denoising techniques do not remove additive Gaussian noise from CT scan images because these spatial filters and denoising techniques [23][24][25][26][27][41][42][43][44][45][46][47][48][49][50][51][52][53] may excel at reducing noise but need help to maintain the integrity of intricate anatomical information.

References

1. Alanazi, T.M.; Berriri, K.; Albekairi, M.; Ben Atitallah, A.; Sahbani, A.; Kaaniche, K. New Real-Time High-Density Impulsive Noise Removal Method Applied to Medical Images. Diagnostics 2023, 13, 1709.
2. Tian, C.; Fei, L.; Zheng, W.; Xu, Y.; Zuo, W.; Lin, C.W. Deep learning on image denoising: An overview. Neural Netw. 2020, 131, 251–275.
3. Kadhim, M.A. Restoration Medical Images from Speckle Noise Using Multifilters. In Proceedings of the 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 19–20 March 2021; Volume 1, pp. 1958–1963.
4. Satra, H.; Gupta, A. Lung Nodule Detection using Segmentation Approach for Computed Tomography Scan Images. Int. J. Forresearch Appl. Sci. Eng. Technol. 2021, 9, 1778–1790.
5. Das, K.P.; Chandra, J. A Review on Preprocessing Techniques for Noise Reduction in PET-CT Images for Lung Cancer. In Congress on Intelligent Systems: Proceedings of CIS 2021; Springer Nature: Singapore, 2022; Volume 2, pp. 455–475.
6. Choi, H.; Jeong, J. Despeckling algorithm for removing speckle noise from ultrasound images. Symmetry 2020, 12, 938.
7. Bharati, S.; Khan, T.Z.; Podder, P.; Hung, N.Q. A comparative analysis of image denoising problem: Noise models, denoising filters and applications. In Cognitive Internet of Medical Things for Smart Healthcare: Services and Applications; Springer: Berlin/Heidelberg, Germany, 2021; pp. 49–66.

8. Rausch, I.; Mannheim, J.G.; Kupferschläger, J.; la Fougère, C.; Schmidt, F.P. Image quality assessment along the one-metre axial field-of-view of the total-body Biograph Vision Quadra PET/CT system for 18F-FDG. Ejnmmi Phys. 2022, 9, 87.
9. Goyal, B.; Agrawal, S.; Sohi, B.S. Noise issues prevail in various types of medical images. Biomed. J. 2018, 11, 1227.
10. Florez-Aroni, S.M.; Hancco-Condori, M.A.; Torres-Cruz, F. Noise Reduction in Medical Images. arXiv 2023, arXiv:2301.01437.
11. Bhonsle, D.; Bagga, J.; Mishra, S.; Sahu, C.; Sahu, V.; Mishra, A. Reduction of Gaussian noise from Computed Tomography Images using Optimized Bilateral Filter by Enhanced Grasshopper Algorithm. In Proceedings of the 2022 Second International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT), Bhilai, India, 21–22 April 2022; pp. 1–9.
12. Hermena, S.; Young, M. CT-scan image production procedures. In StatPearls ; StatPearls Publishing: Treasure Island, FL, USA, 2022.
13. Nakamura, Y.; Higaki, T.; Tatsugami, F.; Honda, Y.; Narita, K.; Akagi, M.; Awai, K. Possibility of deep learning in medical imaging focusing on improvement of computed tomography image quality. J. Comput. Assist. Tomogr. 2020, 44, 161–167.
14. Kaur, A.; Dong, G. A Complete Review on Image Denoising Techniques for Medical Images. Neural Process Lett. 2023, 55, 7807–7850.
15. Mehta, D.; Padalia, D.; Vora, K.; Mehendale, N. MRI image denoising using U-Net and Image Processing Techniques. In Proceedings of the 2022 5th International Conference on Advances in Science and Technology (ICAST), Mumbai, India, 2–3 December 2022; pp. 306–313.
16. Xu, J.; Gong, E.; Ouyang, J.; Pauly, J.; Zaharchuk, G. Ultra-low-dose 18F-FDG, brain PET/MR denoising, using deep learning and multi-contrast information. In Medical Imaging 2020: Image Processing; SPIE: Bellingham, WA, USA, 2020; Volume 11313, pp. 420–432.
17. Kim, B.; Han, M.; Shim, H.; Baek, J. Performance comparison of convolutional neural network-based image denoising methods: The effect of loss functions on low-dose CT images. Med. Phys. 2019, 46, 3906–3928.
18. Sagheer, S.V.M.; George, S.N. A review on medical image denoising algorithms. Biomed. Signal Process. Control 2020, 61, 102036.
19. Kaur, J.; Goyal, B.; Dogra, A. An Analysis of Different Noise Removal Techniques in Medical Images. In Advances in Signal Processing, Embedded Systems, and IoT: Proceedings of Seventh ICMEET-2022; Springer Nature: Singapore, 2023; pp. 579–590.
20. Thakur, R.S.; Chatterjee, S.; Yadav, R.N.; Gupta, L. Medical image denoising using convolutional neural networks. In Digital Image Enhancement and Reconstruction; Academic Press: Cambridge, MA, USA, 2023; pp. 115–138.
21. Abdelhamed, A.; Timofte, R.; Brown, M.S. Ntire 2019 challenge on actual image denoising: Methods and results. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, Long Beach, CA, USA, 16–20 June 2019; pp. 1–14.
22. Vimala, C.; Aruna Priya, P.; Subramani, C. Wavelet transform approach for image processing–A research motivation for engineering graduates. Int. J. Electr. Eng. 2021, 58, 373–384.
23. Zhang, X. A modified non-local means using bilateral thresholding for image denoising. Multimed. Tools Appl. 2023, 1–22.
24. Mayasari, R.; Heryana, N. Reduce Noise in Computed Tomography Images using Adaptive Gaussian Filter. arXiv 2019, arXiv:1902.05985.
25. Ştefănigă, S.A. Fine-Tuned Medical Images Denoising using Median Filtering. Appl. Med. Inform. 2021, 43, 27.
26. Juneja, M.; Joshi, S.; Singla, N.; Ahuja, S.; Saini, S.K.; Thakur, N.; Jindal, P. Denoising of computed tomography using bilateral median-based autoencoder network. Int. J. Imaging Syst. Technol. 2022, 32, 935–955.
27. Ismael, A.A.; Baykara, M. Digital Image Denoising Techniques Based on Multi-resolution Wavelet Domain with Spatial Filters: A Review. Trait. Du Signal 2021, 38, 639–651.
28. Anam, C.; Adi, K.; Sutanto, H.; Arifin, Z.; Budi, W.S.; Fujibuchi, T.; Dougherty, G. Noise reduction in CT images using a selective mean filter. J. Biomed. Physicsengineering 2020, 10, 623.
29. Diwakar, M.; Singh, P. CT image denoising using the multivariate model and its method of noise thresholding in the non-subsampled shearlet domain. Biomed. Signal Process. Control 2020, 57, 101754.
30. Sumijan, S.S.; Purnama, A.W.; Arlis, S. Peningkatan Kualitas Citra CT-Scan dengan Penggabungan Metode Filter Gaussian dan Filter Median. J. Teknol. Inf. Dan Ilmu Komput. 2019, 6, 591–600.

31. Chillaron, M.; Vidal, V.; Verdu, G. Evaluation of image filters for their integration with LSQR computerized tomography reconstruction method. PLoS ONE 2020, 15, e0229113.

32. El-Shafai, W.; Mahmoud, A.; Ali, A.; El-Rabaie, E.; Taha, T.; Zahran, O.; El-Fishawy, A.S.; Soliman, N.F.; Alhussan, A.A.; Abd El-Samie, F. Deep cnn model for multimodal medical image denoising. Comput. Mater. Contin 2022, 73, 3795–3814.

33. Yue, Z.; Zhao, Q.; Zhang, L.; Meng, D. Dual adversarial network: Toward real-world noise removal and noise generation. In Proceedings of the Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, 23–28 August 2020; Part X 16. Springer International Publishing: Berlin/Heidelberg, Germany; pp. 41–58.

34. Xu, J.; Huang, Y.; Cheng, M.M.; Liu, L.; Zhu, F.; Xu, Z.; Shao, L. Noisy-as-clean: Learning self-supervised denoising from corrupted images. IEEE Trans. Image Process. 2020, 29, 9316–9329.

35. Aslam, M.A.; Munir, M.A.; Cui, D. Noise removal from medical images using hybrid filters of technique. J. Phys. Conf. Ser. 2020, 1518, 012061.

36. You, N.; Han, L.; Zhu, D.; Song, W. Research on image denoising in edge detection based on wavelet transform. Appl. Sci. 2023, 13, 1837.

37. Liang, H.; Zhao, S. Salt and Pepper Noise Suppression for Medical Image by Using Non-local Homogenous Information. In Cognitive Internet of Things: Frameworks, Tools and Applications; Springer: Cham, Switzerland, 2020; pp. 189–199.

38. Garg, B. Restoration of highly salt-and-pepper-noise-corrupted images using a novel adaptive trimmed median filter. Signal Image Video Process. 2020, 14, 1555–1563.

39. Gupta, S.; Sunkaria, R.K. Real-time salt and pepper noise removal from medical images using a modified weighted average filtering. In Proceedings of the 2017 the Fourth International Conference on Image Information Processing (ICIIP), Shimla, India, 21–23 December 2017; pp. 1–6.

40. Usui, K.; Ogawa, K.; Goto, M.; Sakano, Y.; Kyougoku, S.; Daida, H. Quantitative evaluation of deep convolutional neural network-based image denoising for low-dose computed tomography. Vis. Comput. Ind. Biomed. Art 2021, 4, 21.

41. Kim, B.G.; Kang, S.H.; Park, C.R.; Jeong, H.W.; Lee, Y. Noise level and similarity analysis for computed tomographic thoracic image with fast non-local means denoising algorithm. Appl. Sci. 2020, 10, 7455.

42. Sarita, D.R.; Saini, J. Assessment of De-noising Filters for Brain MRI T1-Weighted Contrast-Enhanced Images. In Emergent Converging Technologies and Biomedical Systems: Select Proceedings of ETBS 2021; Springer: Singapore, 2022; pp. 607–613.

43. Wang, J.; Tang, Y.; Zhang, J.; Yue, M.; Feng, X. Convolutional neural network-based image denoising for synchronous temperature measurement and deformation at elevated temperature. Optik 2021, 241, 166977.

44. Goceri, E. Evaluation of denoising techniques to remove speckle and Gaussian noise from dermoscopy images. Comput. Biol. Med. 2022, 152, 106474.

45. Majeeth, S.S.; Babu, C.N.K. Gaussian noise removal in an image using fast guided filter and its method noise thresholding in medical healthcare application. J. Med. Syst. 2019, 43, 1–9.

46. Elhoseny, M.; Shankar, K. Optimal Bilateral Filter and convolutional neural network-based denoising method of medical image measurements. Measurement 2019, 143, 125–135.

47. Ebrahimnejad, J.; Naghsh, A. Adaptive Removal of high-density salt-and-pepper Noise (ARSPN) for robust ROI detection used in watermarking brain MRI images. Comput. Biol. Med. 2021, 137, 104831.

48. Li, C.; Li, J.; Luo, Z. An impulse noise removal model algorithm based on the logarithmic image before the medical image. Signal Image Video Process. 2021, 15, 1145–1152.

49. Taufiq, U.A.; Anam, C.; Hidayanto, E.; Naufal, A. Automatic Placement of Regions of Interest using Distance transform to Measure Spatial Resolution on the Clinical Computed Tomography Images: A Pilot Study. Int. J. Sci. Res. Sci. Technol. 2022, 9, 462–471.

50. Arnal, J.; Súcar, L. Fast Method Based on Fuzzy Logic for Gaussian-Impulsive Noise Reduction in CT Medical Images. Mathematics 2022, 10, 3652.

51. Suneetha, A.; Srinivasa Reddy, E. Robust Gaussian noise detection and removal in color images using modified fuzzy set filter. J. Intell. Syst. 2020, 30, 240–257.

52. Li, R.; Zheng, B. A spatially adaptive hybrid total variation model for image restoration under Gaussian plus impulse Noise. Appl. Math. Comput. 2022, 419, 126862.

53. Yuan, Q.; Peng, Z.; Chen, Z.; Guo, Y.; Yang, B.; Zeng, X. The edge-preserving median filter and weighted coding with sparse non-local regularization for the low-dose CT image denoising algorithm. J. Healthc. Eng. 2021, 2021, 6095676.