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Adaptive Gaussian Wiener Filter for CT Scan Images with Gaussian Noise Variance

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Abstract - Medical imaging plays an important role in modern healthcare, with Computed Tomography (CT) being essential for high-resolution cross-sectional imaging. However, Gaussian noise often occurs within the CT scan images and makes it difficult for image interpretation and reduces the diagnostic accuracy, creating a significant obstacle to fully utilizing CT scanning technology. Existing denoising techniques have a hard time balance between noise reduction and preserving the important image details, failing to enable the optimal diagnostic precision. This study introduces Adaptive Gaussian Wiener Filter (AGWF), a novel filter aims to denoise CT scan images that have been corrupted with various Gaussian noise variance without compromising the image details. The AGWF combines the Gaussian filter for initial noise reduction, followed by the implementation of Wiener filter, which can adaptively estimate noise variance and signal power in localized regions. This approach not only outperforms other existing techniques but also showcases a remarkable balance between noise reduction and image detail preservation. The experiment evaluates 300 images from the dataset and each image is corrupted with Gaussian noise variance to ensure a comprehensive evaluation of the AGWF's performance. The evaluation indicated that AGWF can improve the Signal-to-Noise Ratio (SNR) value and reduce the Root Mean Square Error (RMSE) and Mean Square Error (MSE) value, showing a qualitative improvement in CT scan imagery. The proposed method holds promising potential for advancing medical imaging technology with the implementation of deep learning.

Keywords— Image Noise Filtering, Medical Images, Gaussian Filter, Wiener Filter, Signal to Noise Ratio

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I. INTRODUCTION

Medical imaging techniques play a crucial role in the medical field for diagnostic which can allow healthcare professionals to identify abnormalities, such as tumors, infections and internal bleeding and monitor the progression of medical conditions over time. When CT scan (computed tomography scan) was introduced, it was marked as a significant improvement in the medical field. The first CT scanner was developed in the 1970s by Sir Godfrey Hounsfield and Dr. Allan Cormack, leading to a revolutionary breakthrough in diagnostic medicine. The CT scan utilizes X-ray technology to produce highly detailed cross-sectional images of the body. A composite image can be produced by combining a series of X-ray images taken from different angles [1]. Throughout the years, CT scans have undergone significant advancements, including improvements in image quality and faster scanning times. This has shown that CT scan has achieved remarkable diagnosis capabilities.

While CT scan has shown its remarkable diagnostic capabilities in imaging, the presence of gaussian noise can affect the CT scan overall fidelity of diagnostic information. Low level of milliampere-second (mAs) and reconstruction

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algorithms are one of the factors that cause the presence of gaussian noise in the imaging [2]. A low level of mAs may reduce the number of X-ray photons reaching the detector and result in the increase of quantum noise in the X-ray projection data. The reconstruction algorithm affects the quality of the reconstructed CT images if it cannot be adapted with the noise contaminated projection data, and it may amplify the noise and streak artifacts [3].

Many innovative reduction filters have been developed by researchers to enhance the diagnostic quality of CT scan images and reduce the noise within the image. These filters are aimed to effectively suppress noise while preserving important image details, ultimately improving the overall image quality. The author [4] introduced a modified Landweber iteration-based reverse image filtering method and showed superior performance in image deblurring and super-resolution tasks, offering robustness to noise as compared to existing reverse image filtering methods. Dmytro et al. [5] addressed the limitations of conventional filtering methods in image processing software and proposed a model of additive impulse noise and least finite differences (MLFD) method for image filtering, along with an interactive web service for its implementation. It offered a flexible and efficient solution that could outperform existing graphics packages in terms of filtering quality and simplicity. The author [6] introduced a two-dimensional filter based on the Mittag-Leffler function. The filter utilized adjustable parameters to manipulate curve shape and the filter's forgetting factor, while introducing a two-dimensional Mittag-Leffler distribution. The proposed method demonstrated it had more advantages as compared to the conventional filtering techniques.

In the field of CT scan image processing, wiener filter and gaussian filter are widely known and commonly used image filtering techniques [7-17]. While each filter has shown its own advantage, their combination presents a novel approach to address both noise reduction and image enhancement. In this study, a novel method, adaptive gaussian wiener filter (AGWF) has been proposed to filter the noise and enhance the images. The main contribution of the paper can be summarized as follows:

- To propose a novel approach to filter the image noise within the CT scan images.
- To enhance the contrast and brightness of CT scan images.

The paper is organized as follows: Section 2 reviews related work on noise filtering by using gaussian filter, wiener filter and median filter. Section 3 explains proposed methodology for combination of gaussian filter and wiener filter. This section provides a detailed explanation of the combination filter used to filter noise within the image. Section 4 shows the result of the experiments, highlighting areas of strength and weakness in the combination, discusses the implication of these results and compares them with other versions. Lastly, Section 5 concludes the effectiveness of the work and suggests recommendations for further work.

II. LITERATURE REVIEW

A. Image Noise Filtering Using Gaussian Filter

Shaik et al. [18] offered a novel denoising algorithm, which combined the Fast Guided Filter and Discrete Wavelet Transform to effectively remove Gaussian noise from an image. The Fast Guided Filter is utilized to remove noise, but it also inadvertently eliminates some image details. However, the algorithm accurately estimates lost details and merges them with the filtered image to obtain the final denoised output. The results show that the proposed algorithm outperforms these methods such as wiener filter, non-Local means filter, and bilateral filter in terms of Gaussian noise removal.

Kowalski et al. [19] analyzed several smoothing approaches and suggested an algorithm that could utilize the Savitzky Golay, Kalman, and Gaussian filters, as well as mean and median . Kowalski et al. observed their behavior in the context of sensor module signal estimation reliability and processing requirement. Spatial filters and total variance filters, both of which are proposed by Mafi et al. [20] as Gaussian denoising filters, can be used to denoise medical images. The intensity of the filter and that of its neighbors are considered while defining the spatial filters. Although total variation filters assume entire variation, total variation techniques also require that the essential component of the signal gradient be large.

B. Maintaining the Integrity Image Noise Filtering Using Wiener Filter

Baselice et al. introduced Enhanced Wiener Filter (EWF) method for images used in the medical field, such as CT and MRI scans [21]. This method may adapt locally by altering its kernel, unlike the traditional Wiener filter, The EWF integrates greater noise removal with edge and feature restoration. By using a local Gaussian Markov Random Field to represent the output image, this feature is produced. The method has a processing cost that is relatively low to other frequently used filters and necessitates less effort for variable adjustment, making it ideal for quasi-real-time applications. On both created and actual datasets, the overall performance of the proposed method has been evaluated, and when compared to existing methodologies and algorithms, the findings are positive.

A method for applying the Wiener filter to images with an unknown amount of Gaussian noise was put forth by Petkova and Draganov et al.[22]. In contrast to how it is often used, the Wiener filter is given input information before application, and the noise variance is estimated by looking at the distribution of relatively homogeneous areas within the input image [23][24][25].

C. Image Noise Filtering Using Median Filter

The Adaptive Median Filter (AMF) has been introduced by Omer et al. to remove Gaussian noise from CT images while preserving the image boundaries and object-specific information. The results of the general filters show that AMF performs better than the others in terms of efficiency and noise reduction [26].

Chen et al. offered an Adaptive Progressively Weighted Median Filter (APWMF) [27] by utilizing the nearby pixel and three different standard deviation principles to locate the noise. The author used a progressively normalized median filter with an adaptive size region to decrease noise. In the APWMF, the structural elements from a central noisy pixel are used to create the normalized operator. The weighing values, for instance, are often equivalent to the geographic distances when appropriately configured. The method outperforms current filters in terms of noise attenuation, design maintenance, and boundary feature retention.

Shah et al. located and examined a median filter method [28] and its several iterations for minimizing or getting rid of impulsive noise in grayscale images. The performance levels and temporal complexity are assessed. Extensive MATLAB-based experiments were performed on a range of medical images to evaluate the performance of the existing techniques. RMS error (RMSE) and Edge-strength Similarity (ESSIM). Performance evaluation methods like the Peak Signal Noise Ratio (PSNR) and Structural Similarity Index (SSIM) were used to analyze performance aspects.

III. RESEARCH METHODOLOGY

This study proposed AGWF for filtering noise within the CT scan image. Specifically, the combination of the wiener filter and gaussian filter were explored. Figure 1 shows the flowchart of this study.

A. Gaussian Filter and Wiener Filter

The Gaussian filter is a popular smoothing filter used to reduce noise and blur in images [29]. It operates by convolving the image with a Gaussian kernel, which is a two-dimensional Gaussian distribution. The Gaussian filter has a bell-shaped response that assigns higher weights to the pixels closer to the center of the kernel, gradually decreasing the weight for pixels farther away. This weighting scheme results in a blurring effect that reduces high-frequency noise while preserving the overall structure of the image [30]. Equation (1) shows the Gaussian filter formula

$$G(x, y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{x^2}{2\sigma^2}} \tag{1}$$

where σ is the standard deviation of the distribution, assuming the distribution has a mean of zero at x = 0. The distribution is shown in Figure 2. Figure 2 shows a 3D plot of two variables, X and Y. Both are centred on an average value of 0. The X and Y axes represent the values of these variables, while the Z-axis shows the density, which indicates the likelihood of specific X and Y combinations.

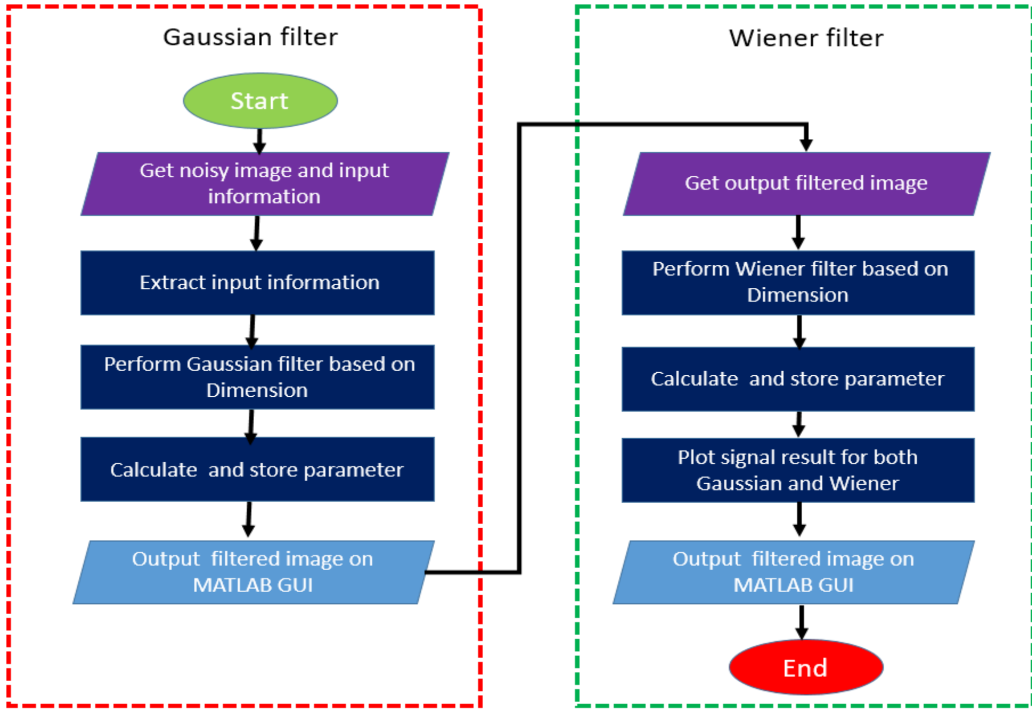

Figure 1. Flowchart of Adaptive Wiener and Gaussian Filter

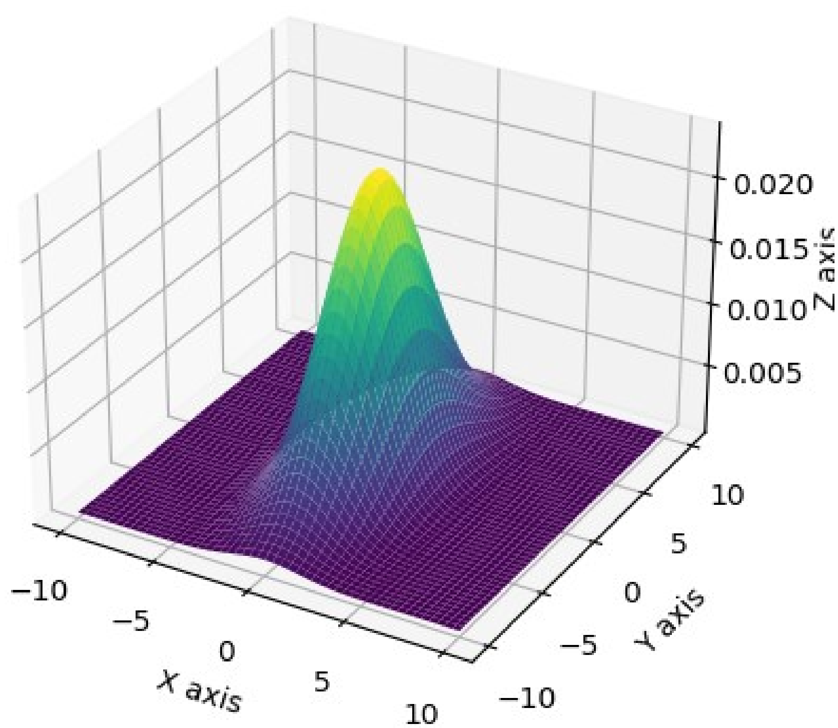

Figure 2. Normal distribution in a 2-dimension space. Both variables are centred in mean 0, with variance 5. X axis shows values of variable 1, Y axis shows values of variable 2, and Z axis, show the density function of data.

The Wiener filter is a linear filter that aims to minimize the mean square error between the original signal and the filtered signal. It is designed to enhance images corrupted by additive noise. By adjusting the filter's parameters, the Wiener filter balances noise reduction and preservation of important image details. Wiener filter equation is shown in Equation (2), (3), and (4).

$$\hat{S}(u,v) = G(u,v)X(u,v) \tag{2}$$

$$G(u,v) = \frac{H*(u,v)P_S(u,v)}{|H(u,v)|^2 P_S(u,v)+P_n(u,v)} \tag{3}$$

$$G(u,v) = \frac{H*(u,v)}{|H(u,v)|^2 + \frac{P_n(u,v)}{P_S(u,v)}} \tag{4}$$

where, $P_s(u,v)$ is the power spectrum of the signal process. $P_n(u,v)$ is the power spectrum of the noise process. Equation (4) can be obtained by dividing through P_s in (3).

B. Adaptive Gaussian Wiener Filter (AGWF)

In this experiment study, the AGWF is the combination of a gaussian filter and a wiener filter. It is aimed to filter the gaussian noise and enhance the CT scan image quality. The CT scan images are input in Digital Imaging and Communications in Medicine (DICOM) format. The CT scan images were corrupted by gaussian noise with various amounts of noise variance, such as 0.01, 0.02, 0.03, 0.04 and 0.05. Figure 3 shows the image corrupted with different variances of noise. The width and height of the images are extracted. The gaussian filter is initially applied to reduce noise and improve the overall quality and resulting a filtered image based on the extracted information [31].

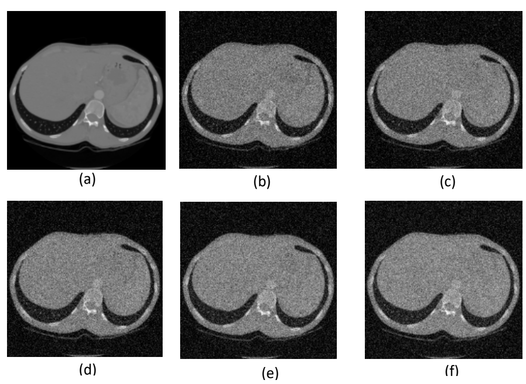

Figure 3. Image corrupted with different gaussian noise variance. a) original image b) corrupted with 0.01 c) corrupted with 0.02 d) corrupted with 0.03 e) corrupted with 0.04 f) corrupted with 0.05

Following that, the Wiener filter is utilized to further enhance the images by effectively removing any remaining Gaussian noise. The Gaussian filter and Wiener filter are applied with different value of sigma (σ) namely, 5, 10 ,15, 20 and 25 to evaluate its performance in reducing noise and enhancing image quality. The selected σ values are used to determine the filter's impact on the final output image. The information extraction is performed on the filtered image and the information is utilized to apply Wiener filter, outputting a further refined filtered image. The Gaussian filter played an important role in filtering noise components and enhancing the clarity of the image. The Wiener filter adaptively estimates the noise characteristics, making it particularly effective in removing the Gaussian noise and enhancing the clarity of the images. The combined use of the Gaussian filter and Wiener filter approach effectively improved the image quality and noise reduction. Figure 4 shows the overall process of the poroposed method

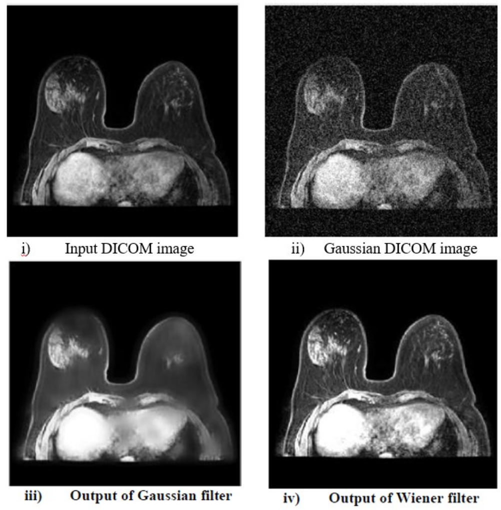

Figure 4. Summary of the process involved in the proposed method, Adaptive Gaussian Wiener Filter (AGWF)

IV. RESULTS AND DISCUSSIONS

A. Dataset

The dataset [32] consists of 300 grayscale images in DICOM format, the size of image is 512 x 512 pixels. The choice of DICOM format ensures compliance with established medical imaging standards, facilitating seamless integration with existing clinical systems and allowing for the inclusion of essential metadata, such as patient information and acquisition parameters. Figure 5 shows a selection of DICOM dataset images.

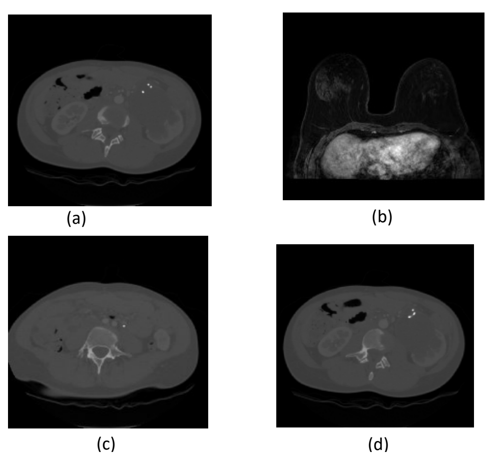

Figure 5. DICOM Dataset Images

B. Quantitative Evaluation Metrics

A comprehensive quantitative evaluation was conducted to assess the performance of the AGWF in this study. The evaluation was aimed to measure the effectiveness of the proposed method in terms of noise reduction and preservation of image details. Metrics such as signal to noise ratio (SNR), mean square error (MSE), peak signal to noise ratio (PSNR) and root mean square error (RMSE) were utilized to quantitatively compare the filtered images against reference images. SNR is used to describe the amount of noise content in the image [33]. These evaluations provided accurate assessments of the superiority and effectiveness of the proposed approach in enhancing the quality of CT scan images. Equation (5) shows the equation of SNR,

$$SNR = 10\log_{10}\frac{\sum_{a=1}^{N_a}\sum_{b=1}^{N_b}\left(x(a,b)\right)^2}{\sum_{a=1}^{N_a}\sum_{b=1}^{N_b}(x(a,b)-y(a,b))^2} \tag{5}$$

where the y(a,b) is the pixel elements from the input images and x(a,b) is the pixel from the noisy image. Equation (6) shows the equation of MSE,

$$MSE = \frac{\sum_{a=1}^{N_a}\sum_{b=1}^{N_b}(x(a,b)-y(a,b))^2}{Size\left(x(a,b)\right)} \tag{6}$$

where x(a,b) is the pixel from the noisy images, y(a,b) is the pixel from the input image, and Size x(a,b) is the noisy image's dimension. The b refers to the height, a represents the breadth of the image. Equation of PSNR is shown in Equation (7),

$$PSNR = 10\log_{10}\frac{max\left(x(a,b)\right)^2}{\sqrt{MSE}} \tag{7}$$

where max x(a,b) is the maximum value of the pixel from that image. The equation of RMSE is shown in Equation (8),

$$RMSE = \sqrt{MSE} \tag{8}$$

C. Result and Discussion

In this study, MATLAB R2016a software is used to explore noise filtering and assess image quality. The MATLAB Image processing toolbox is used to develop image processing workflow. This section discusses the result of the experiment and the analysis from the study. From the dataset that consists of 300 images, 2 images are randomly selected as a representative subset of study, labeled as image A and image B. Figure 6 shows the representation image (Image A and Image B) selected for the study. The evaluation of quality image is an important aspect in this study. Table 1 shows results for image A and B, respectively, after corruption with various noise variance. Based on Table 1, the noise variance increases while the SNR and PSNR value are decreasing. This trend indicated a decline in image quality as the noise variance increases. Moreover, the MSE and RMSE values are increasing. This indicates that the noisy images show larger differences from the clean image, leading to a decrease in image quality and fidelity.

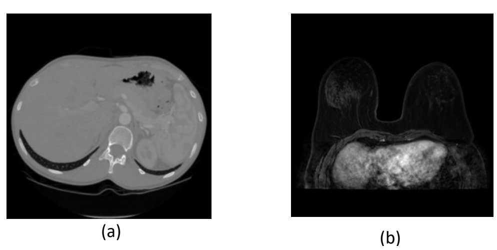

Figure 6. Representative images for the study

Table 1. Image A after corrupted with noise variance.

Noise Variance	Image A Evaluation Metric				Image B Evaluation Metric			
	SNR (dB)	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***
0.01	12.33	20.85	534.87	23.13	17.88	27.02	125.33	11.20
0.02	12.24	20.59	567.38	23.82	17.58	26.72	134.21	11.59
0.03	12.03	20.23	617.26	24.84	17.19	26.25	150.34	12.26
0.04	11.79	19.83	675.71	25.99	16.55	25.33	170.10	13.04
0.05	11.52	19.36	753.35	27.45	16.10	25.05	197.54	14.05

Table 2 and Table 3 show the result of the various existing filters namely median filter, bilateral filter, wavelet transform, anisotropic diffusion, total variation denoising and non-local means across all noise variances ranging from 0.01 to 0.05. The filters are evaluated based on four metrics, namely SNR, PSNR, MSE and RMSE. Based on Table 3, the median filter outperformed the existing filters by achieving the highest SNR and PSNR at 31.51db and the lowest MSE and RMSE at 45.94 and 6.78 respectively, across all the noise variances. The median filter performance decreased as the noise variance increased. Non local means and total variation denoising has the lowest SNR and PSNR at 9.88db and highest MSE and RMSE, peaking at 6678.21 and 81.72 respectively across the noise variances. The non local means and total variation denoising filters are not suitable for denoising CT scan images as its performance maintains the same across all the noise variances. Moreover, the bilateral filter, wavelet transform, and anisotropic diffusion filters showed a moderate performance. The noise variance increased; the performance decreased.

Table 4 and Table 5 show the result of applying the proposed AGWF method with various of σ values to images A and B, respectively under different noise variance. The performance was evaluated using metric namely SNR, PSNR, MSE and RMSE. Based on the presented data on Table 4 and Table 5, it showed that the AGWF method demonstrated its capability to effectively filter the noisy images. It improved the SNR, PSNR, MSE and RMSE value for both images after processing them with Gaussian filters. Both tables showed that the applying AGWF with gaussian σ of 5 achieved the highest performance in terms of the evaluation metrics across all the noise variance while a gaussian σ of 25 resulted in the lowest performance across all the noise variances.

As the σ value increases, the Gaussian filter exhibits the stronger the blurring effect. This can be shown in the SNR and PSNR as the values are decreasing. Therefore, the high value of σ shows the result of a good smoothing effect but reduces the ability to preserve the details of the image. The Wiener filter is employed to mitigate the drawback of the Gaussian filter, specifically its tendency to introduce blurring effects. When the output of the Gaussian filter is passed to the Wiener filter, the PSNR values generally improve, even for higher sigma values. This demonstrates that the Wiener filter is effective in further reducing noise and enhancing the image, compensating for the blurring effect introduced by the Gaussian filter. The Wiener filter can enhance the image quality in the presence of Gaussian noise.

The existing filters do not require the use of gaussian σ because different denoise filters use different types of parameters to control their behavior. In the Gaussian filter, the gaussian σ is used to smooth the image, a high σ can blur the image detail but greatly reduce the noise in the image while a low σ preserves the image while retaining high noise in the image. In the Wilner filter, different σ can adjust the noise reduction and the image preservation performance.

The proposed AGWF method has outperformed the existing techniques throughout the experiment. By using the AGWF, it can greatly improve the image quality by preserving the image detail while reducing the noise within the images. Images with high quality can increase the diagnostic accuracy. With the rapid revolution of the deep learning technology implemented inside the CT scan denoise application, it can significantly improve the CT scan diagnostic accuracy and quality of CT scan images. Deep learning technology has the ability to learn and recognize the pattern of the noise present in the image. It can adaptively classify various noise levels to determine optimal denoising parameters to enhance the image quality.

The filter parameters were meticulously tuned to get optimal results. Manual optimization is not efficient as it is a time-consuming process, thus future study will be considered to explore automated parameter tuning by using deep learning for a more streamlined optimization process. Moreover, future study can use deep learning techniques to denoise the image without using any filters.

V. CONCLUSION

This research project has successfully examined the theory and application of image noise on the SNR value to showcase the proposed method, which is the combination of the Gaussian filter and Wiener filter to conduct noise filtering on medical images. The output findings demonstrate that the Wiener filter can successfully minimize Mean Square Error (MSE), and it also improves the contrast and brightness of the output image. For future work, a deep learning based system may apply an artificial neural network to perform image noise filtering. By leveraging the deep learning technology, the system can learn and adapt to diverse noise patterns, creating a superior filtering performance. However, the system required a large amount of dataset for the training. If the dataset has no sufficient data, the system cannot be trained and will not provide the desired results. This can be the future advancement in medical image noise filtering.

Table 2. Image A evaluation metric with existing method

Filter	Image A (0.01) Evaluation Metric				Image A (0.02) Evaluation Metric				Image A (0.03) Evaluation Metric				Image A (0.04) Evaluation Metric				Image A (0.05) Evaluation Metric			
	SNR (dB)	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***
Median Filter	31.51	31.51	45.94	6.78	30.45	30.45	58.67	7.66	29.57	29.57	71.80	8.47	28.81	28.81	85.56	9.25	28.31	28.31	95.93	9.79
Bilateral Filter	29.21	29.21	77.93	8.83	28.56	28.56	90.49	9.51	28.13	28.13	99.92	10.00	27.96	27.96	104.13	10.20	27.87	27.87	106.23	10.31
Wavelet Transform	20.94	20.94	523.37	22.88	20.61	20.61	565.52	23.78	20.29	20.29	608.51	24.67	19.84	19.84	675.25	25.99	19.35	19.35	755.04	27.48
Anisotropic Diffusion	24.50	24.50	230.76	15.19	23.93	23.93	263.07	16.22	23.35	23.35	300.79	17.34	22.64	22.64	354.32	18.82	21.90	21.90	419.98	20.49
Total Variation Denoising	9.88	9.88	6677.43	81.72	9.89	9.89	6676.18	81.71	9.89	9.89	6675.08	81.70	9.89	9.89	6673.95	81.69	9.89	9.89	6672.77	81.69
Non-Local Means,	9.88	9.88	6678.22	81.72	9.89	9.89	6676.97	81.71	9.89	9.89	6675.87	81.71	9.89	9.89	6674.76	81.70	9.89	9.89	6673.58	81.69

Table 3. Image B evaluation metric with existing method

Filter	Image B (0.01) Evaluation Metric				Image B (0.02) Evaluation Metric				Image B (0.03) Evaluation Metric				Image B (0.04) Evaluation Metric				Image B (0.05) Evaluation Metric			
	SNR (dB)	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***
Median Filter	31.56	31.56	45.37	6.74	30.68	30.68	55.62	7.46	29.61	29.61	71.10	8.43	28.88	28.88	84.08	9.17	28.34	28.34	95.35	9.76
Bilateral Filter	28.42	28.42	93.61	9.68	27.91	27.91	105.13	10.25	27.66	27.66	111.39	10.55	27.75	27.75	109.14	10.45	27.86	27.86	106.48	10.32
Wavelet Transform	21.65	21.65	445.15	21.10	21.17	21.17	496.85	22.29	20.65	20.65	559.60	23.66	20.11	20.11	633.59	25.17	19.59	19.59	714.91	26.74
Anisotropic Diffusion	25.11	25.11	200.71	14.17	24.42	24.42	235.25	15.34	23.65	23.65	280.70	16.75	22.88	22.88	335.23	18.31	22.10	22.10	401.14	20.03
Total Variation Denoising	15.24	15.24	1947.05	44.13	15.24	15.24	1946.89	44.12	15.24	15.24	1946.44	44.12	15.24	15.24	1946.02	44.11	15.24	15.24	1945.59	44.11
Non-Local Means,	15.24	15.24	1947.32	44.13	15.24	15.24	1947.04	44.13	15.24	15.24	1946.60	44.12	15.24	15.24	1946.20	44.12	15.24	15.24	1945.77	44.11

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Table 4 (a). Image A result for 0.01 and 0.02 noise variances

Gaussian sigma (σ)	Image A (0.01) Evaluation Metric								Image A (0.02) Evaluation Metric							
	Gaussian Filter				Wiener Filter				Gaussian Filter				Wiener Filter			
	SNR (dB)	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***
5	36.81	39.9	6.65	2.58	40.17	43.26	3.07	1.75	36.79	39.88	6.68	2.59	40.17	43.26	3.07	1.75
10	31.86	34.95	20.8	4.56	36.13	39.22	7.78	2.79	31.88	34.97	20.72	4.55	36.06	39.15	7.9	2.81
15	28.59	31.68	44.2	6.65	33.65	36.74	13.77	3.71	28.56	31.65	44.5	6.67	33.65	36.74	13.79	3.71
20	26.19	29.28	76.82	8.76	31.95	35.04	20.39	4.52	26.18	29.27	76.98	8.77	31.97	35.06	20.28	4.5
25	24.24	27.33	120.29	10.97	30.59	33.68	27.86	5.28	24.23	27.31	120.69	10.99	30.55	33.64	28.13	5.3

Table 4 (b). Image A result for 0.03 and 0.04 noise variances

Gaussian sigma (σ)	Image A (0.03) Evaluation Metric								Image A (0.04) Evaluation Metric							
	Gaussian Filter				Wiener Filter				Gaussian Filter				Wiener Filter			
	SNR (dB)	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***
5	36.8	39.89	6.67	2.58	40.19	43.28	3.05	1.75	36.81	39.9	6.65	2.58	40.17	43.26	3.07	1.75
10	31.89	34.98	20.67	4.55	36.14	39.23	7.77	2.79	31.86	34.95	20.82	4.56	36.06	39.15	7.91	2.81
15	28.62	31.71	43.91	6.63	33.69	36.78	13.65	3.69	28.62	31.71	43.91	6.63	33.7	36.79	13.62	3.69
20	26.18	29.26	77.03	8.78	31.92	35.01	20.52	4.53	26.19	29.28	76.76	8.76	31.97	35.06	20.26	4.5
25	24.26	27.35	119.77	10.94	30.64	33.73	27.56	5.25	24.2	27.29	121.38	11.02	30.53	33.62	28.27	5.32

Table 4 (c). Image A result for 0.05 noise variance

Gaussian sigma (σ)	Image A (0.05) Evaluation Metric							
	Gaussian Filter				Wiener Filter			
	SNR (dB)	***PSNR (dB)***	***SNR (dB)***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***SNR (dB)***	***RMSE***
5	36.82	39.91	6.64	2.58	40.22	43.31	3.03	1.74
10	31.9	34.99	20.61	4.54	36.17	39.26	7.72	2.78
15	28.6	31.69	44.04	6.64	33.7	36.78	13.63	3.69
20	26.18	29.26	77.02	8.78	31.95	35.04	20.36	4.51
25	24.29	27.37	119.04	10.91	30.68	33.77	27.28	5.22

Table 5 (a). Image A result for 0.01 and 0.02 noise variances

Gaussian sigma (σ)	**Image B (0.01) Evaluation Metric**								**Image B (0.02) Evaluation Metric**							
	Gaussian Filter				**Wiener Filter**				**Gaussian Filter**				**Wiener Filter**			
	SNR (dB)	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***
5	29.86	39.65	7.05	2.65	31.98	41.77	4.32	2.08	29.88	39.68	7.00	2.65	32.04	41.83	4.26	2.06
10	25.36	35.16	19.84	4.45	28.21	38.01	10.29	3.21	25.35	35.15	19.88	4.46	28.16	37.95	10.42	3.23
15	22.12	31.92	41.81	6.47	25.79	35.58	17.99	4.24	22.18	31.97	41.33	6.43	25.89	35.68	17.56	4.19
20	19.73	29.52	72.59	8.52	24.12	33.91	26.43	5.14	19.77	29.56	71.94	8.48	24.14	33.94	26.27	5.13
25	17.88	27.67	111.23	10.55	22.81	32.6	35.73	5.98	17.9	27.69	110.7	10.52	22.82	32.61	35.61	5.97

Table 5 (b). Image B result for 0.03 and 0.04 noise variances

Gaussian sigma (σ)	**Image B (0.03) Evaluation Metric**								**Image B (0.04) Evaluation Metric**							
	Gaussian Filter				**Wiener Filter**				**Gaussian Filter**				**Wiener Filter**			
	SNR (dB)	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***MSE***	***RMSE***
5	29.85	39.65	7.05	2.66	32	41.8	4.3	2.07	29.85	39.65	7.05	2.66	32.02	41.82	4.28	2.07
10	25.33	35.12	20	4.47	28.14	37.93	10.47	3.24	25.34	35.13	19.94	4.47	28.17	37.97	10.39	3.22
15	22.1	31.9	42.01	6.48	25.8	35.6	17.92	4.23	22.11	31.9	41.94	6.48	25.78	35.57	18.01	4.24
20	19.79	29.58	71.58	8.46	24.2	33.99	25.93	5.09	19.75	29.55	72.16	8.49	24.11	33.91	26.44	5.14
25	17.89	27.69	110.8	10.53	22.86	32.65	35.33	5.94	17.88	27.67	111.07	10.54	22.86	32.65	35.33	5.94

Table 5 (c). Image B result for 0.05 noise variance

Gaussian sigma (σ)	**Image B (0.05) Evaluation Metric**							
	Gaussian Filter				**Wiener Filter**			
	SNR (dB)	***PSNR (dB)***	***SNR (dB)***	***RMSE***	***SNR (dB)***	***PSNR (dB)***	***SNR (dB)***	***RMSE***
5	29.87	39.67	7.02	2.65	32.01	41.8	4.3	2.07
10	25.33	35.12	20.01	4.47	28.12	37.91	10.52	3.24
15	22.17	31.97	41.36	6.43	25.85	35.65	17.72	4.21
20	19.73	29.52	72.62	8.52	24.13	33.92	26.37	5.13
25	17.87	27.66	111.4	10.55	22.87	32.66	35.23	5.94

REFERENCES

[1] E. N. Landis and D. T. Keane, "X-ray microtomography," Mater. Charact., vol. 61, no. 12, pp. 1305–1316, 2010, doi: https://doi.org/10.1016/j.matchar.2010.09.012.
[2] A. Aldawood, I. Hoteit, and T. Alkhalifah, "The possibilities of compressed-sensing-based Kirchhoff prestack migration," Geophysics, vol. 79, no. 3, pp. S113–S120, 2014, doi: 10.1190/GEO2013-0271.1.
[3] S. Kuanar, V. Athitsos, D. Mahapatra, K. R. Rao, Z. Akhtar, and D. Dasgupta, "Low Dose Abdominal Ct Image Reconstruction: An Unsupervised Learning Based Approach," 2019 IEEE Int. Conf. Image Process., pp. 1351–1355, 2019.
[4] L. Wang, P. A. Fayolle, and A. G. Belyaev, "Reverse image filtering with clean and noisy filters," Signal, Image Video Process., vol. 17, no. 2, pp. 333–341, 2023, doi: 10.1007/s11760-022-02236-w.
[5] D. Palahin, E. Palahina, and V. Palahin, "Development of Methods for Image Filtering in Noise and their Implementation for a Web Service," Res. Sq., 2023, doi: https://doi.org/10.21203/rs.3.rs-2203260/v1.
[6] I. Petras, "Novel low-pass two-dimensional Mittag-Leffler filter and its application in image processing," TechRxiv, pp. 1–5, 2023, doi: https://doi.org/10.36227/techrxiv.23522907.v1.
[7] W. T. Chan, "Conditional Noise Filter for MRI Images with Revised Theory on Second-order Histograms", International Journal on Robotics, Automation and Sciences, vol. 3, pp. 25–32, Nov. 2021.
[8] J. Portilla, V. Strela, M. J. Wainwright, and E. P. Simoncelli, "Adaptive Wiener Denoising Using a Gaussian Scale Mixture Model In The Wavelet Domain," in Proceedings of the 8th International Conference on Image Processing, 2001, pp. 1–4.
[9] W. T. Chan, "Noise Estimation for MRI Images with Revised Theory on Histograms of Second-order Derivatives", International Journal on Robotics, Automation and Sciences, vol. 5, no. 1, pp. 6–12, Apr. 2023.
[10] M. Kumar, S. K. Mishra, and S. S. Sahu, "Cat Swarm Optimization Based Functional Link Artificial Neural Network Filter for Gaussian Noise Removal from Computed Tomography Images," Appl. Comput. Intell. Soft Comput., vol. 2016, pp. 1–6, 2016, doi: 10.1155/2016/6304915.
[11] Z. Y. Lim and K. S. Sim, "Multi-Color Code with High Data Capacity", International Journal on Robotics, Automation and Sciences, vol. 4, pp. 35–45, Jul. 2022
[12] K. S. Sim, K. K. Law, and C. P. Tso, "Mixed lagrange time delay estimation autoregressive Wiener filter application for real-time SEM image enhancement," Microsc. Res. Tech., vol. 70, no. 11, pp. 919–927, Nov. 2007, doi: https://doi.org/10.1002/jemt.20490.
[13] M. A. Kiani, K. S. Sim, M. E. Nia, and C. P. Tso, "Signal-to-noise ratio enhancement on SEM images using a cubic spline interpolation with Savitzky–Golay filters and weighted least squares error," J. Microsc., vol. 258, no. 2, pp. 140–150, May 2015, doi: https://doi.org/10.1111/jmi.12227.
[14] W. T. Chan, K. S. Sim, and F. S. Abas, "Pixel filtering and reallocation with histograms of second-order derivatives of pixel values for electron microscope images," Int. J. Innov. Comput. Inf. Control, vol. 14, no. 3, pp. 915–928, 2018.
[15] C. K. Toa, K. S. Sim, Z. Y. Lim, and C. P. Lim, "Magnetic resonance imaging noise filtering using adaptive polynomial-fit non-local means," Eng. Lett., vol. 27, no. 3, pp. 527–540, 2019.
[16] Z. X. Yeap, K. S. Sim, and C. P. Tso, "Adaptive tuning piecewise cubic Hermite interpolation with Wiener filter in wavelet domain for scanning electron microscope images," Microsc. Res. Tech., vol. 82, no. 4, pp. 402–414, Apr. 2019, doi: https://doi.org/10.1002/jemt.23181.
[17] T. L. Tan, K. S. Sim, C. K. Tan, and A. K. Chong, "CT image enhancement by colorization for brain infarct detection," Proc. 2011 Int. Conf. Image Process. Comput. Vision, Pattern Recognition, IPCV 2011, vol. 2, no. January, pp. 1030–1034, 2011.
[18] S. S. Majeeth and C. N. K. Babu, "Gaussian Noise Removal in an Image using Fast Guided Filter and its Method Noise Thresholding in Medical Healthcare Application," J. Med. Syst., vol. 43, no. 8, 2019, doi: 10.1007/s10916-019-1376-4.
[19] P. Kowalski and R. Smyk, "Review and comparison of smoothing algorithms for one-dimensional data noise reduction," 2018 Int. Interdiscip. PhD Work. IIPhDW 2018, pp. 277–281, 2018, doi: 10.1109/IIPHDW.2018.8388373.
[20] M. Mafi, H. Martin, M. Cabrerizo, J. Andrian, A. Barreto, and M. Adjouadi, "A comprehensive survey on impulse and Gaussian denoising filters for digital images," Signal Processing, vol. 157, pp. 236–260, 2019, doi: 10.1016/j.sigpro.2018.12.006.
[21] F. Baselice, G. Ferraioli, M. Ambrosanio, V. Pascazio, and G. Schirinzi, "Enhanced Wiener filter for ultrasound image restoration," Comput. Methods Programs Biomed., vol. 153, pp. 71–81, 2018, doi: 10.1016/j.cmpb.2017.10.006.
[22] L. Petkova and I. Draganov, "Noise Adaptive Wiener Filtering of Images," 2020 55th Int. Sci. Conf. Information, Commun. Energy Syst. Technol. ICEST 2020 - Proc., pp. 177–180, 2020, doi: 10.1109/ICEST49890.2020.9232887.
[23] Z. M. Ramadan, "Effect of kernel size on Wiener and Gaussian image filtering," Telkomnika (Telecommunication Comput. Electron. Control., vol. 17, no. 3, pp. 1455–1460, 2019, doi: 10.12928/TELKOMNIKA.v17i3.11192.
[24] J. Wei, S. Ou, S. Shen, and Y. Gao, "Laplacian-Gaussian mixture based dual-gain wiener filter for speech enhancement," 2016 IEEE Int. Conf. Signal Image Process. ICSIP 2016, pp. 543–547, 2017, doi: 10.1109/SIPROCESS.2016.7888321.
[25] S. Peng and L. Lucke, "Hybrid filter for image enhancement," IEEE Int. Conf. Image Process., vol. 1, no. 1, pp. 163–166, 1996, doi: 10.47893/ijipvs.2012.1008.
[26] T. D. Pham, "Estimating Parameters of Optimal Average and Adaptive Wiener Filters for Image Restoration with Sequential Gaussian Simulation," IEEE Signal Process. Lett., vol. 22, no. 11, pp. 1950–1954, 2015, doi: 10.1109/LSP.2015.2448732.
[27] A. A. Omer, O. I. Hassan, A. I. Ahmed, and A. Abdelrahman, "Denoising CT Images using Median based Filters: A Review," 2018 Int. Conf. Comput. Control. Electr. Electron. Eng. ICCCEEE 2018, pp. 1–6, 2018, doi: 10.1109/ICCCEEE.2018.8515829.
[28] J. Chen, Y. Zhan, and H. Cao, "Adaptive Sequentially Weighted Median Filter for Image Highly Corrupted by Impulse Noise," IEEE Access, vol. 7, no. i, pp. 158545–158556, 2019, doi: 10.1109/ACCESS.2019.2950348.
[29] L. Cadena, A. Zotin, F. Cadena, A. Korneeva, A. Legalov, and B. Morales, "Noise reduction techniques for processing of medical images," Lect. Notes Eng. Comput. Sci., vol. 2229, pp. 496–500, 2017.
[30] A. Jain and V. Bhateja, "A Versatile Denoising Method for Images Contaminated with Gaussian Noise," in Proceedings of the CUBE International Information Technology Conference, 2012, pp. 65–68. doi: 10.1145/2381716.2381730.
[31] A. Ampavathi and V. S. T, "Research challenges and future directions towards medical data processing," Comput. Methods Biomech. Biomed. Eng. Imaging Vis., vol. 10, no. 6, pp. 633–652, Nov. 2022, doi: 10.1080/21681163.2021.2018665.
[32] "DICOM Library." https://www.dicomlibrary.com/
[33] K. S. Sim, V. Teh, and M. E. Nia, "Adaptive noise Wiener filter for scanning electron microscope imaging system.," Scanning, vol. 38, no. 2, pp. 148–163, 2016, doi: 10.1002/sca.21250.