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Integrating Bilateral Filtering with Anisotropic Diffusion – A model for Enhancing Diagnostic Quality of Multi-Noise affected COVID-19 Lung Ultrasound Images

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Abstract: Lung Ultrasound (LUS) has become a widely accepted technique for Covid-19 prognosis and diagnosis. This is due to the non-risk factors of ultrasound (US) and the emergence of portable Point of Care equipments. However, multiple types of noise such as gaussian, impulse and speckle noises usually affect ultrasound images. Distinct filters are required for handling each type of noise. Developing a single filter capable of eliminating nearly all types of noise would be highly significant. Considering the characteristics of different filters used for noise reduction, a composite filter has been developed to address all types of noise. The integration of bilateral filters in estimating the conduction coefficient of Anisotropic Diffusion (AD) filters facilitates this accomplishment. To eliminate impulse noise, median filters are incorporated as an intermediate process. The filter performance is quantitatively verified across various types of noise, including mixed Gaussian impulse noise and speckle noise, using performance metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE) and Structural Similarity Index (SSIM). Compared to the existing method of employing individual filters for noise removal, the suggested combined filter shows superior performance in qualitative and quantitative analysis. Resultant images exhibit higher Peak Signal-to-Noise Ratio (PSNR), minimized Mean Squared Error (MSE) and yield improved outcomes. The performance of the proposed filter is evaluated using images affected with speckle noise and resulted in highly improved results. Amidst the rapidly evolving field of artificial intelligence and its application in healthcare, more accurate predictions can be made using these cleaner images, thus improving the performance and reliability of AI algorithms.

Keywords: Anisotropic Diffusion filter; bilateral filter; POCUS; Mixed Gaussian Impulse noise; Speckle noise.

I. INTRODUCTION

The COVID-19 pandemic has affected millions of people throughout the world, with respiratory organs being strongly affected. Diagnosis of COVID-19 and the establishment of prognostic markers are important to determine which patients require admission and to adapt treatment methods accordingly. Real-time reverse transcriptase polymerase chain reaction (RT-PCR) and serology are the popularly used methods in the diagnosis of COVID infection, but they do not provide any data on severity of disease and its prognosis [1]. In this context, thoracic imaging has proven to be a useful diagnostic tool [2]. Although thoracic computed tomography (CT) has been the most studied technique, it is time-consuming and detrimental to human health. At present, there is an increasing amount of literature on the Lung Ultrasound (LUS) use in COVID, both in the diagnosis and prognosis of the disease [3]. There is evidence that LUS may be an effective alternative for diagnosing the disease. This imaging modality is quick, cost-effective, and does not require ionizing radiation. Using point-of-care ultrasound (POCUS) devices, it is possible to conveniently perform examinations at the patient's bedside and repeat them as needed to monitor the progression of the disease [4].

Point-of-care ultrasonography (POCUS) pertains to handheld portable ultrasound instruments that can be used at a patient's bedside. These devices are perfect for COVID-19 scans because they are small enough to be covered completely with a probe cover. Its compactness makes the decontamination process easier. Numerous studies have shown that employing single use plastic sterile probe covers or wrapping the entire device in plastic will suffice to condense the decontamination process. A trained healthcare professional can complete a lung POCUS study within 5 to 10 minutes. It has also been reported that these devices are useful for continuously monitoring COVID-19 patients at home. The noteworthy features of POCUS, including its capacity to connect with smartphones and tablets, assisted diagnosis by artificial intelligence, wireless functionality, rechargeable batteries, and affordability make it a convenient and practical imaging choice, suitable even in remote regions [4-7].

Growing evidence around the world is showing that lung ultrasound examination can detect manifestations of COVID-19 infection [6]. It is used to find important characteristics in the images, including A-lines, B-lines, consolidation, and pleural effusion, all of which help the clinician to monitor and diagnose COVID-19. Subtle

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changes in texture and pattern are frequently observed in COVID-19 manifestations in the lungs. However, these characteristics may be obscured by noise, making it challenging to identify early symptoms of the disease or track its development [8].

Ultrasound images are usually noisy, often lack contrast, and contain artifacts such as speckles, shadows etc. Impulse noises are yet another sort of noise present in ultrasound imaging. Another common type of noise found in medical images is Additive White Gaussian noise. These considerations regarding noise make preprocessing inevitable to enhance the quality of LUS image and prepare them for further processing and segmentation. Even in well-performed scans, imaging distortion and artifacts are often an inescapable reality for POCUS. This results in ultrasound images containing a great deal of "noise" or randomness in the data. [9].

In LUS images, noise reduces the clarity of images, making it difficult to distinguish between healthy and affected lungs. This may affect the precision of diagnostic evaluation. In this context, advanced signal processing algorithms are inevitable for noise reduction in LUS images. Usually, automatic detection after segmentation or relying on deep learning techniques are adopted for fast and reliable interpretation of lung ultrasound images. Prior to applying such techniques, image preprocessing or denoising is always carried out in order to enhance image quality and facilitate diagnosis [10].

Studies show that various types of nonlinear filters [11] can be effectively used to remove such noises. An averaging filter discussed in [8] smoothes the background noise cannot be recommended for such purposes as they smooth edges also. Partial Differential equation based Anisotropic Diffusion (AD) filters are known for their ability to preserve edges in an image during denoising. AD approaches have been used in image processing since 1987 when Perona and Malik [12] introduced a non-linear method of edge preserving smoothing that outperformed the existing traditional linear methods [13]. It can preserve important image features such as edges. While smoothing the rest of the image, it can maintain crisp texture detail at all viewing orientations [14]. Thus, blurring of edges and loss of information can be avoided. In linear filtering such as Gaussian kernel, noise and edges are simultaneously smoothed out. Since ultrasound images are mostly affected by speckle noise and impulse noises [15], a combination of filter structures, which can filter out all types of noises, need to be derived. For suppressing impulse noises like salt and pepper noise, median filter is a good choice. However, it is not effective for reducing Gaussian noise or speckle noise [12]. Anisotropic Diffusion filters are the best choice in removing Gaussian noise and speckle noise from ultrasound images. In this context, a combination of various filters can be integrated in the basic AD algorithm to effectively remove all types of noise. A combination of anisotropic diffusion filters and bilateral filters can be applied in image processing and computer vision applications for enhancement. Such hybrid filtering techniques aim to leverage the strengths of both methods to enhance the quality of images [15]. A cascaded filtering using AD and bilateral algorithms are attempted in [16] and the results for MRI images are presented. Simple AD algorithm is modified by recalculating diffusion constant using bilateral filter is proposed in [17]. A framework of anisotropic median bilateral filter for image denoising is illustrated in [18], where medical images are not discussed. As demonstrated in our previous study [19], a hybrid form of median filter with AD filter has shown promising results both qualitatively and quantitatively for ultrasound images. Thus, the literature suggests that hybrid techniques or the integration of nonlinear filters can enhance the fundamental AD filter performance and allow for more robust noise reduction.

The above constraints lead to the development of a single filter that effectively eliminates various types of noise usually present in LUS images. While preserving essential image features and edges, this filter should not compromise the integrity of the image and should consider the elimination of impulse type of noises or artifacts introduced during the LUS image acquisition process. Bilateral filters are considered as one of the favorable choices in improving the noise performance of AD filters. These filters are very much similar to AD filters so that they can be linked for better performance. Bilateral filter smooth images while preserving strong edges. Several filters utilizing Partial differential equations (PDE) qualitatively attain the same result. This motivated numerous researchers to explore and implement possible links between both approaches [20-22]. Bilateral filtering is a pixel-based approach, in which the denoised version of a given pixel is obtained by the weighted average of its neighbors. The weights are determined by some function that depends on their color/intensity similarity and image distance. In both these approaches, images are smoothed while edges are preserved. Considering the elimination of impulse types of noises, median filter is included as an intermediate stage.

The actual process involved in linking the concepts of these filters can be achieved efficiently by making modifications in conduction coefficient of the AD filter. Here, the decomposed mask images, called parameterized images obtained at an intermediate stage during the process of AD is considered [17]. In the proposed filter, the kernel of bilateral filter is used for the computation of conduction coefficient of AD. An initial processing using median is also done to eliminate the effect of impulse noise.

The distinctiveness of the proposed filter is highlighted by the following key aspects:

•It exhibits better noise reduction across a wide spectrum of noise types. Specifically, this single filter effectively addresses the reduction of both mixed Gaussian impulse noise and the speckle noise of LUS images.

•This work is primarily focused on enhancing lung ultrasound images related to Covid-19. Due to the significant role of POCUS devices during the pandemic, there is an increased utilization of POCUS lung images in this analysis.

•Moreover, this approach integrates the advantages of a bilateral filter into the design of this novel filter, a strategy previously unexplored in ultrasound imaging, particularly in the context of LUS and POCUS images. To substantiate its efficacy, performance comparison using parameters like SNR, MSE and SSIM is done to quantitatively verify the performance of the proposed filter. Both qualitative and quantitative analysis provided better results than using individual filters including median filter or simple AD filters for noise removal.

In a clinical setting, such noise reduction techniques are significant particularly in quantitative analysis for assessing lung involvement in diseases like COVID-19. Noise can distort the appearance of structures within the image, making it difficult to precisely identify and measure relevant features. This introduces inaccuracies in quantitative analysis, potentially leading to misinterpretation of the severity of lung involvement. Since AD and bilateral filters preserve edge information and selectively smooth or reduce noise in images, they can address these challenges related to noise in LUS images.

This paper is organized as follows: Section II discusses theoretical concepts and mathematical formulation on the individual filters related to this work. Development and design of the proposed work is discussed in section III. Section IV demonstrates the testing and validation process involved in evaluating the performance of the proposed filter. An analysis on the performance of the filter based on relevant parameters and interpretation of results is performed in section V. The work is concluded in section VI.

II. THEORITICAL FRAMEWORK

This section discusses the theoretical evolution and methodological formulation of the work. A detailed mathematical analysis of anisotropic diffusion filters is included. The extension of this AD algorithm for estimating diffusion coefficient using bilateral filters necessitates this analysis. The methodology of proposed work and the datasets used in the experiments are also discussed.

A. *Anisotropic Diffusion filters*

First, Pietro Perona and Jitendra Malik pioneered the idea of anisotropic diffusion in 1990 [12]. The basic equation of anisotropic diffusion is represented in (1)

$$\mathrm{I_t} = \mathrm{div}(\mathrm{c}(x,y,t)\nabla \mathrm{I}) = \nabla \mathrm{c}\nabla \mathrm{I} + \mathrm{c}(x,y,t)\Delta \mathrm{I} \qquad (1)$$

Here original Image is I. I_t is the smoothened image via anisotropic diffusion method as the solution of equation (1). Δ is the Laplacian operation, ∇denotes the gradient of the image. *div(...)* is the divergence operator and c(x,y,t) is the diffusion coefficient. c(x,y,t) controls the rate of diffusion and is usually chosen as a function of the image gradient to preserve edges in the image. The diffusion coefficient c(x,y,t) is the primary edge stopping parameter which controls the filtering process and leads to edge preservation. Diffusion constant is represented in terms of conduction coefficient in (2)

$$c(x,y,t) = g(\nabla I) \qquad (2)$$

Where $g(\nabla I)$ is the conduction coefficient function. Two functions were proposed for conduction coefficient as represented by (3) and (4)

$$g(\|\nabla I\|) = e^{-(\frac{\|\nabla I\|}{k})^2} \qquad (3)$$

$$g(\|\nabla I\|) = \frac{1}{1+(\frac{\|\nabla I\|}{k})^2} \qquad (4)$$

where *k* is the edge magnitude parameter.

A four-neighbourhood discrete form of (1) is represented in (5)

$$I(x,y,t+\Delta t) = I(x,y,t) + \frac{\Delta t}{4\sum_{\rho \epsilon z} G(\nabla I(\rho,t))} \qquad (5)$$

where Z is the set of the four neighbourhoods of pixel (x,y), denotes a neighbourhood of (x,y), and $\nabla I(\rho, t) = I((\rho, t) - I(x, y, t)$is the gradient of the image at current time t . The above equation operates recursively over time until it satisfies the defined stopping criterion. Perona and Malik proposed that an ideal diffusion coefficient should satisfy the basic condition that it diffuses more in smooth regions and less around high-intensity transitions. By this approach, noise or unwanted texture are smoothed, while edges are sharpened. The function G is a monotonically decreasing function, defined by $c(x, y, t) = g(\|\nabla I(x, y, t)\|)$. Depending upon the value of the monotonically decreasing function G and the |d| which is the absolute value of gradient, the anisotropic diffusion filtering can be formulated as follows:

- The range of G lies between 0 and 1. For a given value of parameter *k*, G monotonically decreases with |d|. If |d|→ 0 then G→1 indicating isotropic diffusion (Gaussian filtering); if |d| → ∞ then G→ 0 the diffusion flow is halted, and the edges of image are preserved.
- For a fixed value of |d|, G monotonically increases with *k*, which means that *k* controls the generosity of the anisotropic diffusion filter. Higher values of k are more inclined to facilitate a diffusion process that smoothens the image and diminishes noise. Conversely, for lower value of k, the diffusion process is restricted, and image features are better preserved.

Advantage of this technique is that it reduces noise and preserves the edges so that crisp edge features will be obtained. The discretized form of Perona –Malik Anisotropic diffusion equation is given in (6)

$$I_{t+1}(s) = I_t(s) + \frac{\lambda}{\eta_s} g_k(|\nabla I_{s,p}|)||\nabla I_{s,p}| \quad (6)$$

Where I is the discretely sampled image, s the pixel position, in the 2D grid, t denotes iteration step, g represents conductance function and k corresponds to gradient threshold parameter [14]. Constant $\lambda \in (0,1)$ decides rate of diffusion and η_s denotes the spatial 4-pixel neighborhood of s, η_s ={N,S,E,W} are the neighboring pixels of s in North, South, East and West directions. This approach is preferred due to its low computational complexity.

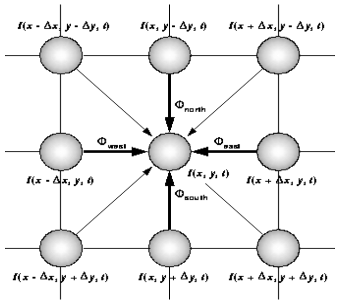


Fig. 1 Neighborhood Visualization of 2D discrete diffusion

Visualization of 2D discrete diffusion is given in fig.1. Degraded image with each pixel replaced by median value is applied to the AD filter so that partial removal of impulse noise can be achieved. In this 8 Neighborhood Visualization, η_s ={N,S,E,W, NE, SE, SW, NW} are the neighboring pixels of *f(x,y)* in North, South, East, West, Northeast, Southeast, Southwest, Northwest directions.

B. Bilateral filter

Aurich and Weule's research in 1995, focused on nonlinear Gaussian filters, eventually led to the later re-emergence of bilateral filters. Its name was given by Tomasi and Manduchi in 1998. Bilateral filtering is a non-linear technique that can smooth the image while retaining its edges. It replaces the intensity of each pixel with a weighted average of intensity values from nearby pixels. The bilateral filter takes into account the difference in value with the neighbours to preserve edges while smoothing. Each neighboring pixel is assigned to a weight comprising a spatial component, which penalizes distant pixels, and a range component, penalizing pixels exhibiting differing intensities. The combination of both components ensures that only neighboring pixels exhibiting similar characteristics contribute to the outcome. The fundamental concept behind bilateral filter is that for a pixel to influence another pixel, it should not only occupy a nearby location but also have a comparable value. This unique combination preserves sharp edges while reducing noise.

The bilateral filter, denoted by F[·], is defined by (7) as

$$F[I]_p = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(\| p - q \|) G_{\sigma_r}(|I_p - I_q|) I_q \quad (7)$$

Here, W_p is a normalization factor. It ensures pixel weight sums to 1.0.

σ_s and $\sigma_{r\,specifies}$ the extent of filtering for I. $G\sigma_s$ represents a spatial Gaussian weighting parameter that diminishes the influence of distant pixels. $G\sigma_r$ denotes a range Gaussian factor, reducing the influence of pixel q when intensity value is different from I_p.

C. Median Filter

Median filtering is a nonlinear method employed for image noise reduction. In this method, every pixel value is derived by selecting the median value among neighboring pixels in a designated window. Thus, the result is the middle value within the sorted neighborhood. When an image is considered, each pixel in the filtered image represents the median brightness of its respective neighbourhood.

Median is a kind of image smoothing technique like Gaussian filtering. Almost all the smoothing techniques including Gaussian filter negatively affect edges and thus cause blurring in the image. Preserving integrity of edges is critically important for visual appearance of the image. For moderate levels of Gaussian noise (medium tailed distribution), median filter per-forms better than Gaussian filter and do not affect edges. However, when faced with substantial noise levels, its performance does not improve significantly [23]. Median filters are more effective for removing salt and pepper noise, which is a type of impulsive noise.

From the equations and analysis presented, it is clear that Anisotropic Diffusion is a method that selectively smooths or reduces noise in images while preserving edge information. It works on the local orientation of structures within the image and adjusting the degree of smoothing based on the orientation of edges. This aids in maintaining sharp boundaries between different tissues or structures in the LUS image while reducing the impact of noise. Bilateral filters consider both spatial and intensity similarities between neighboring pixels. Working on a weighted average of nearby pixels, with the weights determined by both spatial distance and intensity similarity, it preserves edges and fine details by attenuating noise while retaining important structural information. By considering local image features and intensity variations, anisotropic and bilateral filters maintain sharp edges and boundaries, preventing blurring or loss of detail that could compromise the accuracy of quantitative measurements. All these features ensure that quantitative analysis retains critical information about the morphology and characteristics of lung tissue. Both these filters effectively reduces speckle and Gaussian noises [14,16]. Median filters are incorporated here with the aim of removing impulse noise. In LUS images, impulse noise can occur due to various factors, such as artifacts introduced during the image ac-quisition process, electronic interference, signal transmission errors etc. These noises appear as sudden and isolated spikes in pixel intensity within the ultrasound image. The median operation effectively removes impulse noise because outliers caused by noise have minimal impact on the median value calculated from neighbouring window pixels thereby improving the overall quality and reliability of LUS imaging for clinical use. Combined effects of these filters can contribute to the reduction of almost all types of noise usually found in LUS images as illustrated in result section.

III. DEVELOPMENT OF THE PROPOSED FILTER

AD filtering is a widely accepted filtering algorithm for ultrasound image denoising. It preserves edges and boundaries without affecting homogenous regions. During the execution of the AD algorithm, it produces nonlinear and space variant transformations of the original US image. These are called parameterized images or mask images. In equations (2) and (3), $\|\nabla I\|$ is the parameterized image. Equation (2) reveals that the diffusion constant depends on conduction coefficient. Further, the conduction coefficient depends on the parameterized images. Hence, these parameterized images play a significant role in the estimation of the diffusion constant.

For ultrasound images corrupted with the various noises as discussed in section 1, the decomposed mask images or parameterized images contain biased pixel intensities caused by noise. This may lead to an inaccurate estimation of the diffusion constant. Consequently, this could degrade the efficacy of the AD filtering process. Therefore, a modification in the AD approach is proposed to overcome this issue. This means that the local gradients that are arguments of the conductance function are now computed with a smoothed and edge preserved bilateral version of image in every iteration. Computing in this method can eliminate the artifacts that are preserved in the resultant image when using basic AD scheme.

In the proposed filter, the initial step involves decomposing multiple noise-contaminated ultrasound images into their corresponding set of mask images. Thus, before the estimation of conduction coefficient, these mask images are subjected to Bilateral Filtering [24]. This effectively reduces the noise present in mask images. The resultant mask images are subsequently employed to compute the conduction coefficient using equation (4). This conduction coefficient is then utilized by the AD algorithm to suppress noise and preserve structure of the Ultrasound images.

Flowchart in Fig.2 illustrates the implementation of the proposed filter.

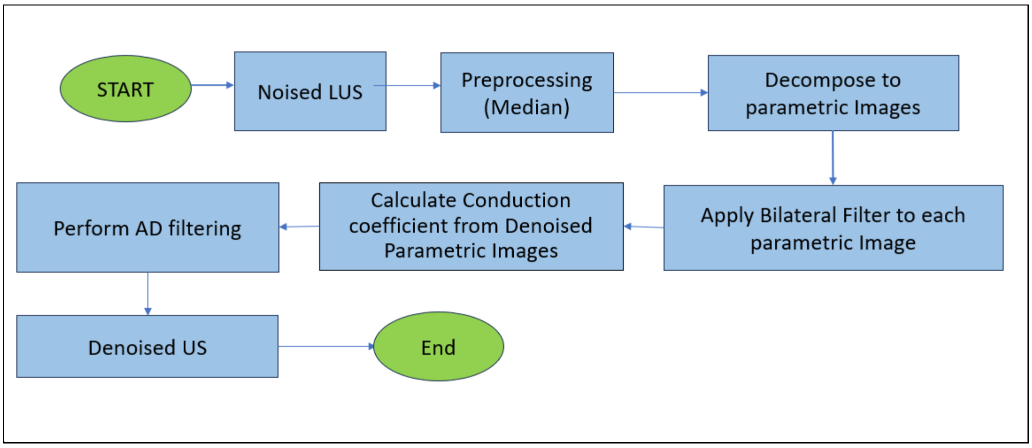


Fig.2. Flowchart of the proposed AD filtering Algorithm

The detailed design flow of proposed modified AD filtering algorithm is illustrated below:

Step1: Add multiple noise to the LUS image I(x,y,t)`

Step2: Preprocessing using median filter.

Step3: Define convolution masks for η_s={N,S,E,W}

Step4: Construct Parametric Images,$\|\nabla I\|$using the masks

Step5: Use kernel of bilateral filter to process parameterized images

Step6: Calculate conduction coefficient with equation (4) , ie.,

$$g(\|\nabla I\|) = \frac{1}{1+(\frac{\|\nabla I\|}{k})^2} \qquad (8)$$

Step7: Perform AD filtering with the modified conduction coefficient calculated from *step*6 using equation (5).

As mentioned by Perona in [12] the constant k can be fixed either by hand or using some noise estimators like Canny. The figures presented here represent the results with k value fixed at 15 on an empirical basis. The experiment is conducted initially with 10 iterations and performance is confirmed through more iterations of 20 and 30. The illustrations presented in various figures depict the outcome from 15 iterations.

IV. TESTING AND VALIDATION

The objective involves designing a composite filter by combining nonlinear filters and validate it against existing methods. Design procedure is discussed in sections II and III. The work is implemented using Matlab R2018b. Testing and validation process verify its effectiveness by comparing performance against existing relevant methodologies or works in the field. For validating the proposed filter, images used are contaminated with mixed Gaussian impulse noise of standard deviation 0.02 and impulse noise of density 0.02 in order to study the response of different filters to gaussian impulse noise. For speckle noise analysis, zero mean speckle noise with variance 0.04 is used. Here the efficacy of the proposed filter is being evaluated by comparing it with other nonlinear filters such as the median filter and simple AD filter. This comparative analysis aims to assess the superiority of the newly designed composite filter in handling the given task. Both quantitative and qualitative analysis and comparison are carried out. *Qualitative performance analysis* is done by visually comparing the output images. *Quantitative comparison* employs metrics such as Mean Squared Error (MSE), Signal-to-Noise Ratio (SNR), and Structural Similarity Index (SSIM). These metrics enable a numerical assessment of the filters' performance based on factors like image fidelity, noise reduction, and similarity to the original image.

A. Quantitative Analysis

In this study, diverse performance quality metrics are employed to analyze the efficacy of the proposed method in comparison to the simple AD filter and median filter. The chosen metrics serve to evaluate the system's efficiency by comparing parameters like Signal-to-Noise Ratio (SNR), Mean Square Error (MSE), and Structural Similarity Index (SSIM). SSIM is a method for measuring the similarity between two images. The SSIM index is a quality measure of one of the images being compared while the other image is considered as of perfect quality. Maximum value of SSIM is 1, reachable only in the case of two identical images [25].

The SNR, MSE and SSIM are computed using the formula

$$SNR = 10\log_{10}\frac{\sum_{p=1}^{N}\sum_{q=1}^{N} v(p,q)^2}{\sum_{p=1}^{N}\sum_{q=1}^{N}(u(p,q)-v(p,q))^2} \tag{9}$$

$$\mathrm{MSE} = \frac{1}{NXN}\sum_{p=1}^{N}\sum_{q=1}^{N}\big(u(p,q)-v(p,q)\big)^2 \tag{10}$$

$$SSIM(x,y) = \frac{(2\mu_p\mu_q+C_1)(2\sigma_{pq}+C_2)}{(\mu_p^2+\mu_q^2+C_1)((\sigma_p^2+\sigma_q^2+C_2)} \tag{11}$$

μ_p, μ_q, σ_p,σ_q, and σ_{pq} are the local means, standard deviations, and cross-covariance for image I(p,q)

For evaluation, POCUS images from the dataset of https://github.com/jannisborn/covid19_pocus_ultrasound is used. A sample set of 10 images is shown in Fig.3. From the dataset, 50 POCUS images of the CO VID-19 are analyzed. Initially, 15 iterations are done for simple AD and the proposed filters. Significant improvement in the chosen parameters of quantitative analysis is observed for all the images, yielding favorable results even with variations in the number of iterations. The results are analyzed in detail in section V.

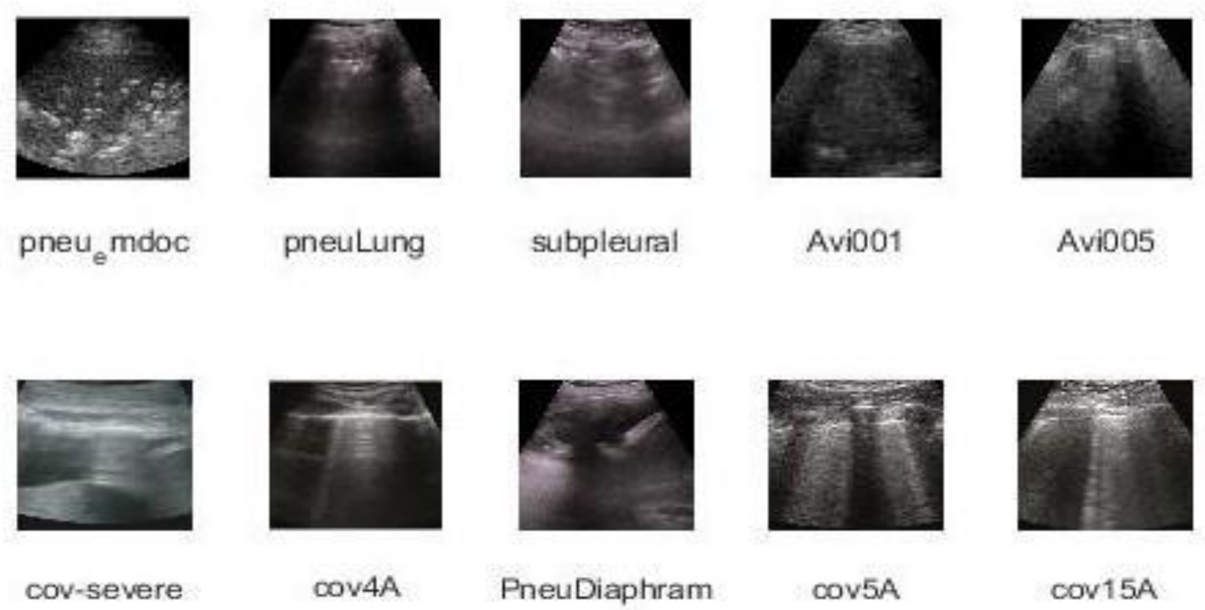


Fig. 3 Test images used in experiments

V. Analysis and Interpretation

A. Response of LUS images to Mixed Gaussian Impulse Noise

The initial verification of the noise filtering process involves the Covid-19 POCUS image named cov_severe, which has dimensions of 367x367 pixels. This image is contaminated with Gaussian noise having a standard deviation of 0.02 and impulse noise density of 0.02. The proposed filter's output is compared with that of a median filter and a simple AD filter. Figure 4 depicts the output of cov_severe image for Simple AD filter, Median filter and proposed AD filter. These results correspond to 15 iterations undergone for simple AD and proposed filter.

Observing the resulting images reveals that while the simple AD filter struggles to effectively eliminate mixed Gaussian impulse noise, the visual quality of the output images from the proposed combined bilateral AD filter appears superior. This improvement is quantitatively verified using various metrics.

(a)	(b)	(c)	(d)	(e)

Fig. 4 Response of various filters (a)cov_severe POCUS image (b) image corrupted by mixed Gaussian impulse noise (c) AD response of median filter (d)) simple AD(e)output of proposed bilat_AD

The ability of filter to produce desired results is evaluated using multiple LUS (Lung Ultrasound) images. Figure 5 displays the outcome obtained with cov_15A image.

(a) (b) (c) (d) (e)

Fig. 5 filter Response of various filters (a)COV_15A LUS image (b) image degraded with mixed Gaussian impulse noise (c)response of median filter (d)simple AD (e)output of proposed bilat_AD filter

Results indicate that the proposed filter exhibited enhancements across all the 50 images. Additionally, visual quality of the suggested filter appears to have improved. Comparing the outputs, the results from the median filter seem to be superior to those from the simple AD filter for all samples. However, the combination of bilateral and AD filters demonstrated superior performance over median filters, both in qualitative visual assessment and quantitative measures.

1) Quantitative Analysis

The quantitative evaluation with the parameters SNR, MSE, and SSIM in Table I gives these parameter values corresponding to five sample images affected by mixed Gaussian impulse noise. The parameters were measured after 15 iterations using Simple AD filter, median filter, and the proposed filtering method. For all images, the value of SNR is significantly higher compared to other filters. The MSE is at its minimum, and the structural similarity index (SSIM) is also favorable. Results are sketched in Fig. 6. Figure 7 illustrates a comparison of the SSIM values. For all images, we can see that the output of the proposed filter is better in terms of SNR, MSE and SSIM.

TABLE I QUANTITATIVE ANALYSIS OF LUS IMAGES ON MEDIAN, AD & PROPOSED FILTERS FOR MIXED GAUSSIAN IMPULSE NOISE

Image	**Parameters**	**Mixed Gaussian Impulse noise**		
		Median filter	***Simple AD filter***	***Proposed BilatAD filter***
Cov_severe	SNR (dB)	10.5	8.7	25.9
	MSE	22.76	33.8	0.169
	SSIM	0.51	0.15	0.57
Pneu_lung	SNR (dB)	10.7	5.8	36.884
	MSE	18	19	0.052
	SSIM	0.4	0.1	0.4
Cov_5A	SNR (dB)	10.6	8.3	35.73
	MSE	22	36	1.8
	SSIM	0.53	0.2	0.68
Cov_15A	SNR (dB)	10	9.4	34.85
	MSE	21.8	30	0.084
	SSIM	0.53	0.15	0.56
Sub_pleu	SNR (dB)	10	8	33.96
	MSE	19.5	28	0.10
	SSIM	0.44	0.12	0.46

The resultant quantitative parameter values depicted in Table I for five selected images is compared in Fig. 6 and Fig. 7. A comparison of MSE and SNR values is sketched in fig. 6

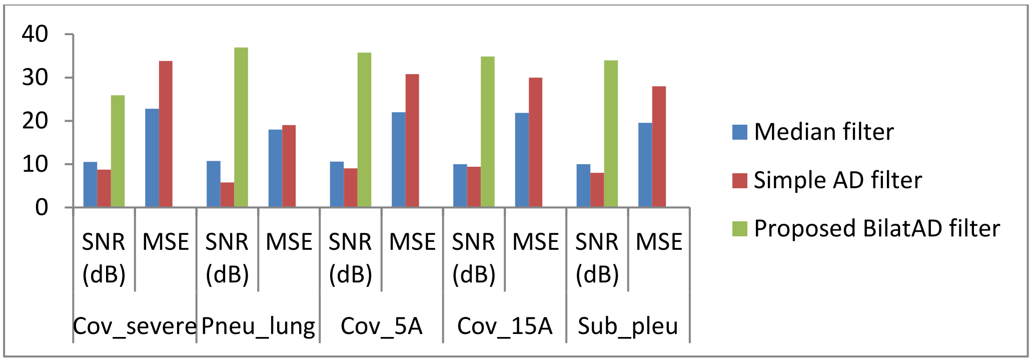


Fig 6 Comparison of SNR, and MSE using 5 sample images with mixed Gaussian impulse noise. Results of median, simple AD and proposed Bilat_AD filtering scheme

For all the test images, the proposed filter exhibits excellent performance with highest signal to noise ratio and minimum MSE. Comparison of SSIM is sketched in Fig. 7.

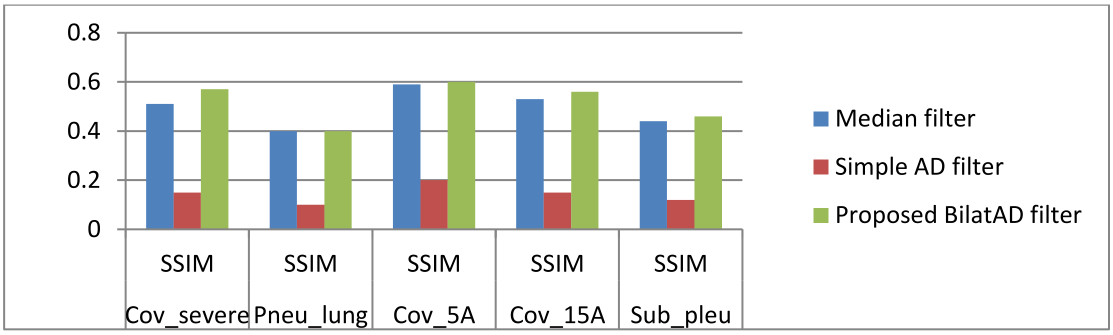


Fig. 7 Comparison of SSIM values

Herealso, the proposed filter's performance is superior compared to simple AD filter and median filter. Median filters give a comparable output better than simple AD filter.

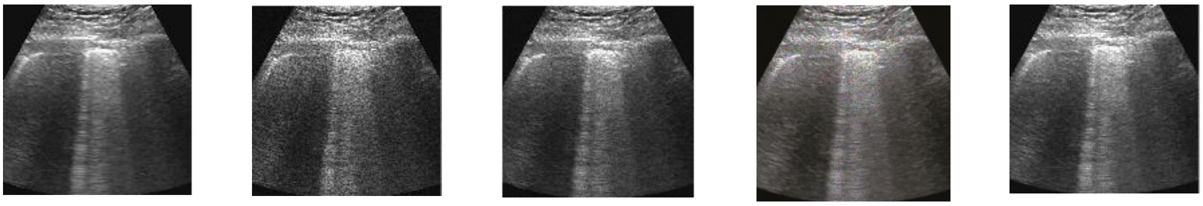
B. Response to Speckle Noise

Speckle noise represents a prevalent noise type found in ultrasound images. It significantly impacts image contrast resolution by affecting edges and fine details and makes diagnostic more difficult. Anisotropic diffusion (AD) filters are known for their effectiveness in eliminating speckle noise from such images. The proposed filter leverages the strengths of both bilateral and AD (Anisotropic Diffusion) filters. The assessment aims to determine how effectively this combined filter mitigates the impact of speckle noise in the LUS images, potentially improving their quality and aiding in better interpretation and analysis. The analysis involves evaluating the performance of the proposed filter on Lung Ultrasound (LUS) images affected by zero-mean speckle noise with a variance of 0.04. According to the results shown, speckle removal can be effectively accomplished by processing the image with the proposed filter modified by incorporating bilateral filtering kernel in computing conduction coefficient.

Figures 8 and 9 depict a comparative analysis showcasing the outputs generated by three distinct filters: the simple AD filter, the median filter, and the proposed bilateral_AD filter for Cov_severe POCUS image and COV_15A image affected by speckle noise.

(a) (b) (c) (d) (e)

Fig. 8 Responses of various filters for cov_severe POCUS Image for Speckle noise



(a) (b) (c) (d) (e)

Fig. 9 Responses of various filters for Cov_15A LUS Image for Speckle noise. (a)Original image b) speckle noised (c)median filter output p (d) Simple AD filter output(e)Proposed bilat_AD filter output

The outcomes demonstrate an enhancement in visual quality. In contrast to the result obtained with mixed gaussian impulse noise, an improvement in visual quality of image is observed for simple AD filter as opposed to median filter. However, the proposed filter performs superior compared to the two other distinct filters. Throughout these experiments, the process is validated by executing 10 iterations initially and further confirmed through additional verification using 20 and 30 iterations. This iterative approach helps assess the impact and effectiveness of the filtering process across varying iteration counts, ensuring consistency and validating the robustness of noise removal.

1) Quantitative Analysis

Table II illustrates quantitative evaluation with the parameters SNR, MSE, and SSIM when zero mean speckle noise with variance 0.04 is used to degrade the image.

TABLE II. SPECKLE NOISE - QUANTITATIVE ANALYSIS OF MEDIAN FILTER, AD FILTER AND PROPOSED FILTER

Image	Parameters	Speckle Noise		
		Median Filter	*Simple AD filter*	*Proposed filter*
Cov_severe	SNR (dB)	7.5	13	18
	MSE	44	40	3.9
	SSIM	0.56	0.4	0.6
Avi_005	SNR	9.5	13	19.2
	MSE	28	5.5	2
	SSIM	0.73	0.82	0.81
Cov 15A	SNR (dB)	9.5	13	19
	MSE	28.28	19.9	3
	SSIM	0.7	0.63	0.74
Pneu_lung	SNR (dB)	12	15.8	20.9
	MSE	12	5	1.63
	SSIM	0.86	0.8	0.85

Fig 10 and Fig.11 sketches the variation of SNR, MSE and SSIM as per Table II.

Results show that Simple AD filters outperform median filters in the speckle filtering process, despite their poor performance in decreasing gaussian impulse noise. This result emphasizes the ability of AD filters in effectively reducing speckle noise. The most significant inference is that the proposed filter supersedes median and simple AD filters in speckle noise removal, achieving highest SNR and lowest MSE.

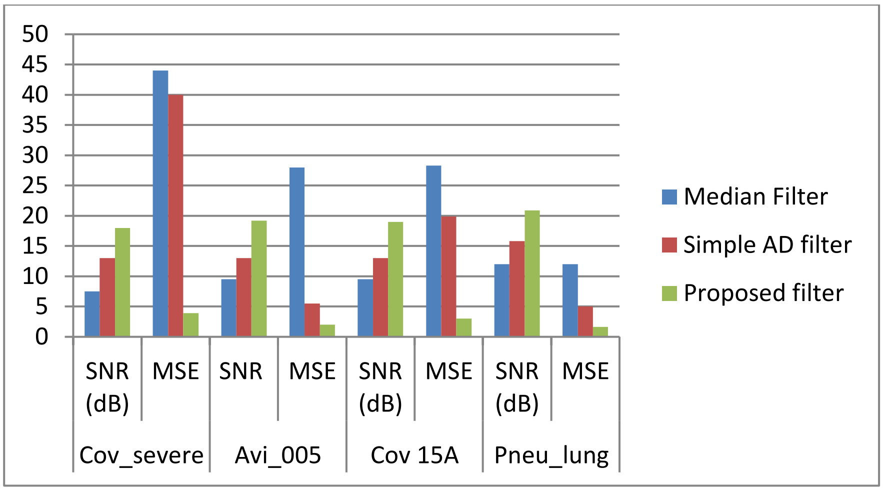


Fig.10 Comparison of SNR and MSE using 4 sample images corrupted with Speckle noise. Results of median, simple AD and proposed bilat_AD filtering schemes

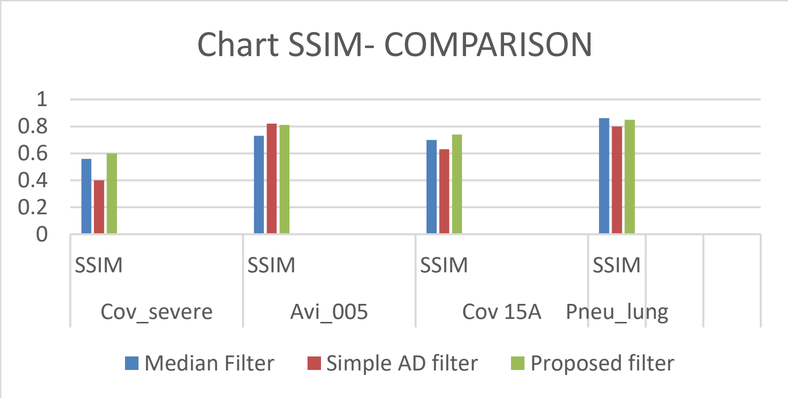


Fig.10 Comparison of SSIM using 4 sample images corrupted with Speckle noise. Results of median, simple AD and proposed bilat_AD filtering schemes

Figures depicted in this section clearly illustrate that the proposed Bilat_ AD filter produces better results than individual filters in terms of SNR, MSE and SSIM. Regarding the removal of mixed gaussian impulse noise, considering all the examined images, the proposed filter provides the highest SNR with a maximum value of 36.9. In contrast, the individual filters only yield a maximum value of 10. Similarly, MSE is as small as 0.169 for the proposed filter when compared with the least value of 18 for other filters. Favorable results are obtained for SSIM also. For speckle noise, the proposed filter achieves a maximum SNR of 20.9 while median and simple AD filters gave only 15.8 and 12 respectively. MSE has a significant improvement with maximum of 3.9, 44 and 40 for proposed, median and simple AD respectively, with SSIM values improved compared to mixed gaussian impulse response. In general, the proposed filter is superior in performance to other noise reduction filters both qualitatively and quantitatively.

The necessity of applying denoising algorithms is more obvious whenever the LUS image under consideration is of poor quality. In such cases, it is often recommended to perform X-ray or CT imaging of the lungs further to rule out the possibility of COVID-19. However, both modalities utilize ionizing radiation, which can be harmful to health. To a certain extent, the need for additional X-ray or CT scans can be mitigated by preprocessing the noisy image with image denoising techniques. In situations where the patient is a child or an expectant woman, further CT or X-ray scans may not be advisable. The importance of employing an efficient denoising algorithm becomes even more prominent in such scenarios.

VI. Conclusion

This paper introduces an innovative approach to noise filtering utilizing anisotropic diffusion filters. The smoothing and structure preservation properties of anisotropic diffusion filters and the noise reduction and edge preservation features of bilateral filtering are combined to optimize the efficiency. Mixed Gaussian impulse noise and speckle noise are taken into account. Qualitative analysis demonstrated enhancement in visual quality. The parameters such as SNR, MSE, and SSIM are used for quantitative analysis. Results are found to be superior to using individual filters for noise removal. Further research and experimentation are open on this area on optimizing the parameters of both filters or investigating different integration strategies to further understand and enhance the effectiveness of these filters in denoising applications. The dependence of anisotropic diffusion process on its parameters like conductance function, gradient threshold, stopping time of iterative process etc. suggest that the algorithm presented here can be examined on other methods in literature which optimizes the parameters. With the emergence of fast advancing and readily accessible Machine learning (ML) and Deep Learning (DL)Technologies for automated disease detection and other performance metrics relevant to these technologies, the proposed algorithm can play a crucial role in the preprocessing stage to enhance diagnostic accuracy.

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