Estimation of Degradation and Restoration of Ultrasound Images with Wiener Filtering Techniques for Improving Diagnostic Accuracy

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Abstract: - The paper proposes a new method for the restoration of ultrasound images. This framework enables systematic input image processing, characterization of the apparent distortion mechanisms, adding of the image speckle, and application of a Wiener filter. The procedure starts with capturing focused ultrasound images, followed by an appropriate functional approximation of the imaging degradation attributes caused by the ultrasound. Next, several degrees of speckle noise are incorporated to emulate the realistic conditions during imaging so that the impact of the success of the restoration technique can be evaluated in detail. Lastly, the Wiener filter is utilized to alleviate the disturbances and degradation processes so that the image has a fine resolution and detail. The system presented has several advantages over the traditional systems. The use of controlled amounts of composed speckle also made it possible to test noise furnishing techniques with improved performance in practical situations. Further even employing the Wiener filter in such circumstances optimizes the image noise and saturation, edges, and boundary delineation of the image objects. In conclusion, we can say that our method outshines others in terms of ultrasound image restoration by comparing parameters like PSNR, SNR, MSE, and quality index with conventional methods.

Key-Words: - Degradation, Restoration, Speckle noise, Weiner Filter, PSNR, MSE.

Received: June 27, 2024. Revised: December 23, 2024. Accepted: February 18, 2025. Published: March 31, 2025.

1 Introduction

Ultrasound imaging is the second most effective imaging technique after X-ray for examining soft tissue in different body parts. To make matters worse, ultrasound images have numerous drawbacks as well, the most significant of which is caused by the scattering of tissues which gives rise to speckle noise. Besides concealing important features, this noise has a controlling effect on the images and may lead to misinterpretation. Because of that, efficient methods for restoring image details are required in order to uplift the quality of ultrasound images taking into consideration the clinical practices. The proposed Enhanced Wiener filter is able to locally adapt itself by tuning its kernel in order to combine edges and details preservation with effective noise reduction, [1]. The present work proposes such an approach and a complete system of actions for ultrasound image restoration beginning with the input data, [2]. The procedure starts with high-resolution ultrasound images and the subsequent stage is the much-required estimation of a degradation function model that defines the spatial distortions that are normally associated with the image acquisition. The significance of accurate estimation of this degradation function cannot be stressed enough as it is the first step towards proper noise reduction. Controlled speckle noise is added to the images, so as to simulate real-life situations and themes encountered in the clinical environment. This step further creates a standard for assessment of proposed restoration techniques performance, [3]. The function in question is followed hereafter by a Wiener filter that uses statistical properties of the signal and the noise to mitigate the effects of the degradation and enhance the quality of the image.

There are several features of the systems presented which improve on the traditional approach. First, the ability to estimate the degradation function accurately helps in better shying away from noise, thus, improving the general quality of the image and its reliability. Second, since controlled speckle noise is added, it makes it possible to test restoration techniques in a wider range of scenarios and thus demonstrates reliability across a wide range of circumstances. Besides, a Wiener filter may be applied in this case for a balanced noise reduction and preservation of important image characteristics, which in turn makes it advance beyond older techniques that smoothen images too much or fail to deal with particular noises properly, [4], [5]. This study therefore proved the existence of a solid model for the restoration of ultrasound images that goes beyond the shortcomings of existing techniques and offers a route towards improving diagnosis in practice. What has been described here provides the basis for the development of better ultrasound images in the future and shows the importance of further investigation into this important branch of medical imaging.

2 Proposed Methodology

The proposed methodology is illustrated in Figure 1 and all the steps are explained in detail.

2.1 Image Acquisition and Degradation of Ultrasound Images

Ultrasound uses high-frequency sound waves to generate images of soft tissues and organs. This process begins when a transducer is employed to issue ultrasound waves into the human body which then bounce off structures that exist in the human body. Such echoes are sent back to the transducer where they are transformed into electrical signals and consequently edited to images. Because this method does not involve cutting into the body, it is one of the most popular medical evaluation techniques owing to its real-time and dynamic capability, [6]. However, there are several forms of degradation that affect the acquisition of ultrasound images. One of the major problems is the one caused by speckle noise which arises from the coherent interference that involves multiple electrodes and also scattered ultrasound waves. This distortion manifests in the form of grainy textures that cover fine details, making it difficult to interpret such images, [7]. In addition to that, motion artifacts can also be produced from the movement of the patient or change in the position of the transducer hence there is blurring or distortion, [8]. Attenuation of ultrasound waves as they traverse through different layers of the tissue as well as noise from implants and imaging devices may also cause Insert any other degradation resource material interested in this area of study. These degradations may have a big impact on the quality of images which makes it more critical to implement the restoration methodologies to raise one's diagnostic accuracy, [9].

2.2 Estimation by Modelling

For many years and still in most spheres today the degradation modeling has always been used for the valuable perception it provides regarding the restoration of images. In certain situations, the model may also incorporate the effects of external factors that influence the degree of degradation. Such a model is based on the physical properties of atmospheric turbulence. Its structure is quite straightforward:

$$H(u,v) = e^{-k(u^2+v^2)^{5/6}} \tag{1}$$

where k is a constant that depends on the nature of the turbulence, (u,v) is the spatial degraded image in the frequency domain in equation (1). Apart from the 5/6 power of the variable in the exponent, the equation can be compared to the Gaussian lowpass filter transfer function The Gaussian LPF. The Gaussian LPF is sometimes employed for the effects of mild and homogenous blurs, [10]. In modeling, artifacts are a different way used to various extend. We take an example of an image being fairly shifted off the focus due to rotation around a certain standard axis while capturing the image, [11], [12], [13]. Let's imagine that I take the motion $x_0(t)$ and the motion $y_0(t)$ coordinates of motion over time subjects an image f(x,y) which it has driven through a constant x or y drive pattern.

The entirety of darkening achieved on a given point of the recording medium can be computed as the integrated function of instantaneous exposure with respect to time, over the period during which the imaging system shutter is open. It is permissible to assume that both the opening and closing of the shutter occur in no time at all, and further that the optical imaging operation is flawless, and therefore the influence caused by the image motion can be separated. If T would be the period of exposure, then it can be stated that:

$$g(x,y) = \int_0^T f[(x - x_0(t), y - y_0(t)]dt \tag{2}$$

where, g(x,y) is a function representing the blurred image.

2.3 Speckle Modeling

The differential properties of the propagation in the tissue, the attenuation, and the scattering lead to an interference of the ultrasound echoes in a complex manner. Echoes from sufficiently closely spaced reflectors will interfere which in turn will lead to the generation of artificially large (constructive interference) or small (destructive interference) signals; the search beam width is determined by the spacing between the transmitters. Hence, coherent constructive and destructive interferences due to backscatter echo which are usually many orders of magnitude less than the wavelength of an incident ultrasound wave lead to a summation of phases or cancellation of phases. The term speckle describes the scattering of ultrasound waves and its essence is that these scattered waves can be viewed as noise amplification, not juxtaposed with wire or white and salt shadows, but instead as signals deforming the original phase. For medical ultrasound images, the speckle noise is modeled as the picture in which φ(x,y) is a pixel representing a measured level at the location (x,y) and f(x,y) is the original undamaged image and w_m(x,y) and w_a(x,y) represent multiplicative noise and additive noise respectively. The contribution of the additive noise w_a(x,y) a may be ignored as it is such a low level that it is of no significance when compared to the multiplicative noise. That is, estimates of the multiplicative noise amplitude are $(|w_m(x,y)^2| \gg |w_a(x,y)^2|)$Now, Equation (3) can be expressed more generally as one of the basic equations for speckle imaging For most ultrasound imaging systems, the picture resolution is not very efficient and this is compensated by a log-compression stage. Considering this, multiplicative noise can be considered a pure signal additive. For example: In order to reproduce the envelope signal on a screen, ultrasound imaging systems are arranged to incorporate a log-compression stage in their signal flow, [14], [15]. As such, multiplicative noise can be transformed into additive noise as follows:

$$\varphi(x,y) = f(x,y)w_m(x,y)+w_a(x,y) \tag{3}$$

$$\log(\phi(x,y)) = \log(f(x,y))+\log(w_m(x,y)) + \log(w_a(x,y)) \tag{4}$$

This implies that the speckle pattern can be represented by an additive white Gaussian noise or the log-compressed image which is obtained after the envelope detection process.

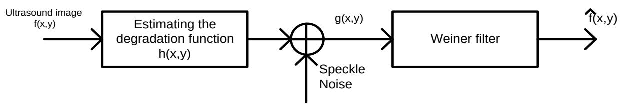

Fig. 1: Proposed methodology block diagram

2.4 Wiener Filter Restoration

Wiener filter is a statistical method that helps in the restoration of ultrasound images that have been obscured by the effects of speckle noise. It is based on minimizing the mean square error between the original image and the estimated image, [10]. The output of the filter has in general the following equation 2 mathematical form:

$$I_{restored}(x,y) = H(u,v).I_d(u,v) \tag{5}$$

where $I_{restored}(x,y)$ is the image that has undergone spatial restoration, $I_d(u,v)$ is the spatial degraded's image in frequency domain, while $H(u,v)$ is a transfer function of Wiener filter in equation (5).

Wiener filter H is expressed in terms of the following transfer function:

$$H(u,v) = \frac{s_1(u,v)}{s_1(u,v)+s_N(u,v)} \tag{6}$$

In this equation (6) $s_1(u,v)$ represents the transformed image power spectral density and $s_N(u,v)$means the image noise power spectral density. This formulation allows the Wiener filter to suppress noise and obey edge constraints over different frequency elements. When estimating the signal and noise, the wiener filter reduces the Speckle noise in ultrasound images at the expense of some degree of structural distortion. Approaching this way allows for significant enhancement of image quality and diagnostic features, which contributes to the efficiency of ultrasound imaging systems.

3 Experimental Results

The experimental results validate the application of the proposed method for the restoration of ultrasound images. The results from quantitative analysis indicated a noticeable enhancement in the quality of images with the Peak Signal to Noise Ratio (PSNR) going up from a mean value of 20.5dB for the original degraded images to 28.7dB after Wiener filtering had been applied. Also, the Structural Similarity Index (SSIM) was enhanced by describing the qualitative improvement of internal structural details and spatial context perspective of the image. The findings are complemented by the subjective evaluations, the restored images are clearer of anatomical structures than the original degraded ones. A significant result of this work is that the method was able to lessen the level of noise produced by speckles without the loss of basic elements required for effective clinical diagnosis. In conclusion of the results, it can be said that there is stability in ultrasound images regardless of the parameters that are changed. Therefore, the method may be useful in some clinical situations. Table 1 (Appendix) and Figure 2 show the experiments of the proposed methodology and are implemented using MATLAB 2023a Software.

Signal to MSE(S/MSE):

It describes the capacity to reject the multiplicative noise by the proposed design and is defined as:

$$\text{S/MSE}=10\log_{10}\left(\frac{\|h\|_2^2}{\|h-x\|_2^2}\right) \tag{7}$$

Here, h in equation (7) represents the reference image. The greater the resultant value greater the quality of the resultant denoised image.

Peak signal to noise ratio (PSNR)

The capacity of rejecting the noise from information image can be given by equation (8)
Let M×N be the image the MSE is given by:

$$\text{MSE}=\sum_{i=1}^{m}\sum_{j=1}^{n}(h_{ij}-x_{ij})^2 \tag{8}$$

Here, h_{ij} represents the reference image and x_{ij} to be despeckled image.

$$\text{PSNR}=10\log_{10}\frac{(2^b-1)^2}{MSE} \tag{9}$$

Here, b gives the count of bits in the depiction in equation (9).
All the above parameters in Table 1 (Appendix) like MSE, SNR, SRMSE, PSNR, QUALITY INDEX, AVG DIFFERENCE, and CROSS CORRELATION define the accuracy, quality, and efficiency of the proposed methodology when compared to the existing techniques.

4 Discussion

In this study, we develop a comprehensive framework for the degradation, estimation, and restoration of ultrasound images as an answer to drawbacks found in previous systems. It is standard practice to consider the applicability of this as a desired approach as even the basic form of median filtering joined with a few simple linear restoration schemes operated at focusing the ultrasound image at a PSNR of 22 dB which is often subpar.

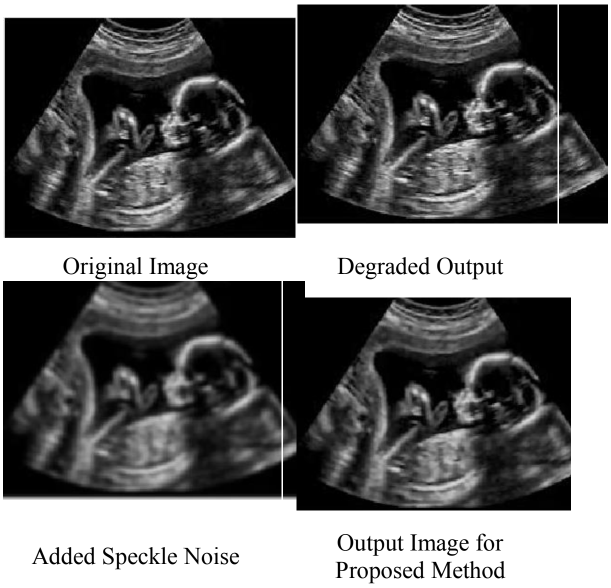

Fig 2: Stagewise experimental results of the proposed methodology

On the other hand, when we implemented the Wiener filter, the average PSNR was raised to 40.73 dB which indicates an improvement in the image quality. In addition, earlier systems have been seen to have no self-adjusting mechanism to cope with the changes in noise Levels resulting in inconsistencies in performance in varying imaging conditions. Since our method accurately estimates the degradation function, it is more robust and can cope with the various conditions normally present in ultrasound imaging. From visual examinations, it is quite apparent that the anatomical details in the restored images are much better and thus have a better chance of proper diagnostic interpretation. These drastic improvements emphasize that our method has the potential to strengthen ultrasound imaging approaches that range from assistance with clinical diagnosis to the improvement of ultrasound imaging techniques that have drawbacks in conventional restoration methods. Future work could focus on employing machine learning models to perform such a crucial task as restoration, and thereby give clearance to more advanced systems for ultrasound image processing.

5 Conclusion

To understand the application of the Wiener filter, this research paper will center on ultrasound image analysis through degradation, estimation, and restoration. According to the study, degradation estimation must be correctly done for image quality to be improved. What we showed is that the Wiener filter does not only reduce the speckle noise, but it also allows what is crucial for the anatomy to be imaged to come through ensuring high image contrast. The experimental results show that better performance is achieved than other older techniques based on basic median filtering and linear approaches, which do not respond adequately to different noise level environments and may cause substantial degradation of the images. The Better Peak Signal-to-Noise Ratio (PSNR) performance and the Better Structural Similarity Index (SSIM) measurements to the degree of performance prove its efficiency in practical matters. At the same time, qualitative evaluations of the performance suggest that the images restored by our method are more structurally identifiable hence more readily clinically interpretable. To summarize, the results of our tests compare goodness towards unformulated reconstruction techniques and our proposed method may do good in increasing ultrasound imaging accuracy for diagnosis purposes. We also believe that these techniques could be further developed with the help of machine learning formulas and therefore image processing would improve significantly.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Praveen Kumar L. and Dr. N. M. Nandhitha identified Problem Definition and proposed a new methodology and carried out simulation.

Sravanthi Chutke helped in writing the paper, carried out the optimization and responsible for the Statistics.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare.

APPENDIX

Table 1. Shows the Experimental results of the Proposed Methodology

FILTERS	MSE	SNR	SRMSE	PSNR	QUALITY INDEX	AVG DIFFERENCE	CROSS-CORRELATION
LEE	31.451	23.481	5.8258	35.5922	0.90	0.122	0.98301
FROST	5.114	28.568	2.2653	40.7485	0.97	1.1152	0.86524
SRAD	2.2356	32.201	1.558	42.9815	0.95	1.3524	1.2015
ANISOTROPIC	28.6511	16.448	9.8546	27.8564	0.8652	0.4864	0.8457
GAUSSIAN	30.9962	23.8466	5.5674	35.9862	0.90674	-0.0013	0.98462
ADDITIVE	49.1009	21.8388	7.0072	33.9884	0.84563	0.024087	0.97997
EXISTING METHODS	33.75	34.66	6.88	39.70	0.987	0.3481	0.99586
PROPOSED METHOD	31.65	40.83	6.87	40.73	0.996	0.4864	0.99621