Impact of Training Data Quality on Deep Speckle Noise Reduction in Ultrasound Images

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ABSTRACT

Speckle noise reduction is an essential step in ultrasound image analysis. One of the challenges in speckle noise reduction is removing noise without significantly losing image detail. Various studies have been conducted using image processing and deep learning approaches. This research offers a simple framework using a deep learning method, which shows that the quality of the images used in the training process influences the performance of the denoising results using the trained network. The training data in the form of ultrasound images in this study was processed separately using various speckle noise reduction methods. We also compare with one of the pre-trained networks, namely denoising convolutional neural networks (DnCNNs). The research shows that denoising results using training data processed using the hybrid speckle noise method provide high image edge preservation performance. The tests in MATLAB reveal a significant reduction in the speckle noise of the ultrasound image, with a peak signal-to-noise ratio of 20.68 dB, a mean structural similarity index measure (MSSIM) of 0.83, and Pratt's Figure Of Merit metric indicating an edge preservation index value reaching 91.76%. Reducing speckle noise using this approach takes less time, ensuring well-maintained edge information and clear visibility of image details, making it applicable for ultrasound diagnosis.

CCS CONCEPTS

• **Applied Computing**; • **Life and Medical Science**; • **Health Informatics**;

KEYWORDS

speckle noise, denoising, deep learning, ultrasound image

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1 INTRODUCTION

The primary issue in ultrasound image processing lies in the quality of the images, particularly those obtained from portable ultrasound machines. Speckle noise is one of the disturbances that needs to be eliminated. Ultrasound machines employ high-frequency sound waves for image acquisition, and the coherent nature of this imaging technique leads to the creation of multiplicative artifacts known as speckle noise. Speckle noise manifests as granular patterns, and its characteristics vary depending on the specific biological tissue being imaged. The interference of back-scattered signals gives rise to speckle noise, which can seemingly enhance resolution beyond the capabilities of the imaging system. In most cases, the noise component is more pronounced than the fine details of the tissue parenchyma, thereby diminishing the visibility of the targeted tissue area. Consequently, the primary challenge in despeckling is to effectively remove the noise without adversely affecting the microstructure and edges of the image.

Generally, methods for reducing speckle noise can be categorized into two main groups: multi-resolution approaches and spatial filtering approaches. Spatial filtering for noise reduction can be further categorized into three subtypes: linear filtering, non-linear filtering, and anisotropic diffusion [8]. Filters employed in spatial filtering methods encompass average filters, median filters, and adaptive filters like Lee filters, Frost filters, Kaun filters, Wiener filters, and bilateral filters. On the other hand, multi-resolution techniques encompass wavelet transform [5, 18–20], curvelet transform [10], contourlet transform [10, 16], brushlet transform [1], and shearlet transform [2]. Beyond these two categories, there are various other techniques, including the fractional-order adaptive regularization primal–dual algorithm [15], the unbiased non-local means method [14], the fuzzy logic-based coefficient of variation approach [12], and the filter based on fractional order integration and fuzzy logic [13]. In reference [6], a denoising method for ultrasound images is proposed, comprising five steps: discrete wavelet transform (DWT), bilateral filtering, thresholding, followed by anisotropic diffusion, and inverse wavelet transform. This approach enhances the preservation of image edges, consequently impacting the effectiveness of the image edge-based ultrasound image segmentation phase [3].

Numerous studies have employed convolutional neural networks (CNNs) for the purpose of image denoising. In one instance, a study referenced as [4] categorizes 30 image denoising network models into two main groups: CNN denoising for general images and CNN denoising for specific images. Another study, denoted as [7], focused on reducing speckle noise in brachial plexus nerve ultrasound images and implemented five deep learning networks for this task. These networks include the Dilated Convolution Autoencoder Denoising Network (Di-Conv-AE-Net), Denoising U-Shaped

Net (D-U-Net), BatchRenormalization U-Net (Br-U-Net), Generative Adversarial Denoising Network (DGan-Net), and CNN Residual Network (DeRNet). The study also compared their performance with traditional algorithms such as Lee, Frost, and Bilateral filtering. Additionally, [21] introduced denoising convolutional neural networks (DnCNNs) designed to handle Gaussian denoising with unknown noise levels.

The most commonly used performance measurement in noise reduction methods is PSNR or MSE, which is used to see how much noise is reduced in an image. However, the main challenge in despeckling, namely, to filter out the noise content without affecting the microstructure and edges, the level of edge preservation is also a significant concern. Performance measures for the level of edge maintenance in noise reduction techniques include Pratt's FOM measure, whose value ranges from 0-1, where the greater and closer to the value 1, the higher the level of edge maintenance. In research in recent years, computing time has become a major focus, especially for real-time applications and large image sizes such as 3D images. So, developing speckle-noise reduction techniques, primarily to obtain high performance in eliminating noise while maintaining details or edges and fast computing times, is still challenging. Following the study above, combining the wavelet decomposition technique with several filtering techniques can provide good performance. Of the several filtering techniques, the anisotropic diffusion method is the choice to integrate with the bilateral filtering technique because the excellent edge preservation rate reaches more than 90%.

While the DnCNN method introduced by [21] leverages residual learning and batch normalization to accelerate training and enhance denoising effectiveness, the extensive layer count, which extends to 59 layers, results in a sluggish denoising process for 3D images. Therefore, in our study, we introduce a speckle noise reduction strategy that employs a more compact network model comprising only nine layers, as described in [9]. We use training data that has been processed (preprocessed) to improve noise reduction performance with the classic denoising algorithm. In this research, we show the effect of training data quality on improving edge preservation rate performance. A smaller layer size also causes the image denoising computing time on 3D ultrasound images to be faster. Based on this description, this research has two main contributions, namely (1) investigating the role of the quality of the training data used in the denoising network by applying various denoising algorithms and (2) applying a network that has been trained to reduce speckle noise in 3D ultrasound images.

2 METHODS

2.1 Dataset

The ultrasound imagery employed in this study was sourced from a portable ultrasound apparatus, comprising a 64-element convex probe transducer, a beamforming circuit, and a computer or laptop running the Windows operating system for data processing. The training dataset included a total of 70 images, distributed as follows: 17 images of the fetal abdomen, 38 images of the fetal head, and 15 images of the fetal femur. To assess the denoising speed, we utilized a 3D fetal ultrasound image with dimensions measuring 370x395x302, 532x416x53 and 532x416x26.

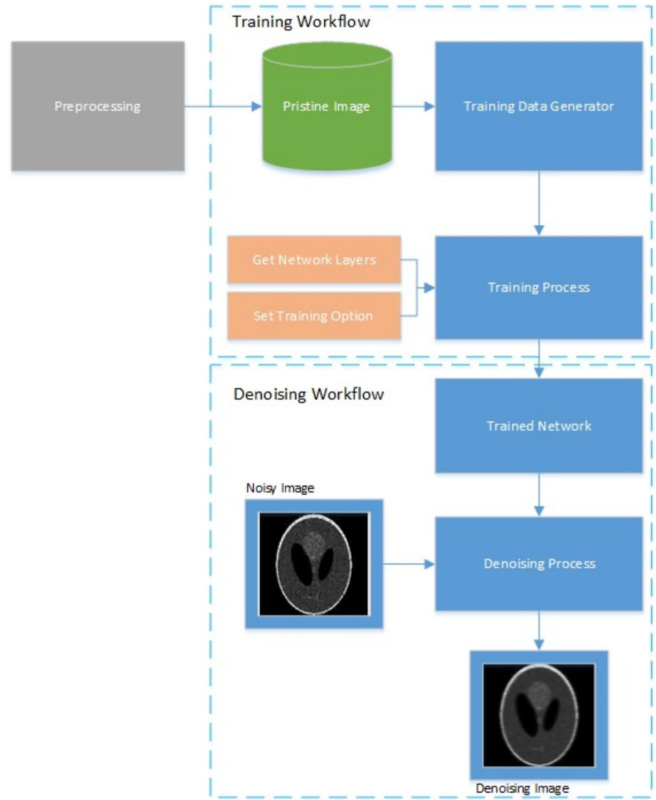

Figure 1: The proposed scheme for speckle noise reduction

2.2 Proposed Scheme

Figure 1 shows the entire proposed process, divided into two major parts: training workflow and denoising workflow. The training data is passed through the preprocessing stage in the training workflow by applying the classic image denoising method. In this research, we tested several traditional denoising algorithms such as those in the study [3], namely the Lee Filter, Frost Filter, Bilateral Filter, Speckle Noise Anisotropic Diffusion (SRAD), Dual-Tree Wavelet (DTW), and Hybrid Speckle Noise Reduction Method. The training data generator generates a noisy patch image of size 50x50. A noisy patch image is generated by randomly cropping the pristine image and adding zero mean Gaussian white noise with a standard deviation of 0.1.

In the training phase, a shallow denoising network layer [9], as depicted in Figure 2, is employed with the Adam optimizer and training settings using a Mini Batch Size of 128. Following the training of this denoising network using a straightforward network structure, the denoising process involves the use of an activation function to identify noise or high-frequency anomalies in a corrupted image. Subsequently, the noise is subtracted from the distorted image, resulting in a noise-free image.

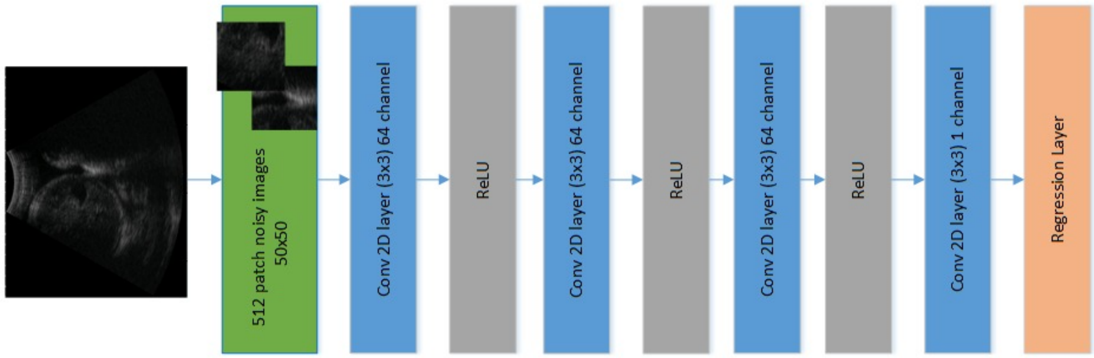

Figure 2: Simple denoising network layer

2.3 Performance Evaluation

Four metrics were employed to quantitatively assess the effectiveness of the speckle noise reduction technique. The evaluation primarily relies on two fundamental parameters for assessing image enhancement methods, which are Peak Signal To Noise Ratio (PSNR) and Root Mean Square Error (RMSE) [12, 13]. Additionally, a metric known as Pratt's Figure Of Merit (FOM) [17] was used to gauge the extent of edge preservation resulting from the noise removal process. Furthermore, the quality of image restoration outcomes as perceived by the human eye was evaluated using the Structural Similarity Index Measure (SSIM) [11]. These measurement criteria include:

1. The Mean Square Error (MSE) measurement calculates the mean discrepancy between the intensity values of the reference and restored images by squaring the differences and then taking the average. The Root Mean Square Error (RMSE) is derived from the MSE measurement and is calculated as the square root of MSE. The formula for MSE is as follows.

$$MSE = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}\left(g\left(x,y\right) - f\left(x,y\right)\right)^2 \tag{1}$$

with $g(x,y)$ is the intensity value of the restoration image, $f(x,y)$ is the intensity value of the reference image at coordinates (x,y), where $x=1,2,...,M$, and $y=1,2,..,N$, with M and N is the number of rows and number of columns of the image

2. The Peak Signal Noise Ratio (PSNR) measurement quantifies the ratio between the maximum gray level value in the image and the disparity between the gray level value in the restored image and that in the original image. A higher PSNR value indicates superior image quality. The PSNR is calculated using the following formula:

$$PSNR = 10\log_{10}\left(\frac{\left(\max I\right)^2}{MSE}\right) \tag{2}$$

3. The Structural Similarity Index Measure (SSIM) is a metric used to evaluate the quality of image restoration as perceived by the human eye. It amalgamates three key factors: the loss of correlation, variations in lighting, and alterations in contrast. The Mean Structural Similarity Index Measure (MSSIM) represents the average SSIM value between two images, typically a reference image and a restored image. MSSIM values range from 0 to 1. A higher value, closer to 1, suggests that the image quality is essentially identical, meaning that the restored image quality matches that of the reference image. The following equation expresses the SSIM index between signal x and signal y:

$$SSIM\left(x,y\right) = \left[l(x,y)^{\alpha}.c(x,y)^{\beta}.s(x,y)^{\gamma}\right] \tag{3}$$

where $l(x,y)$ is luminance comparison, $c(x,y)$ is a contrast comparison function, and $s(x,y)$ is structure comparison function, each of which is defined as follows:

$$\begin{aligned} l\left(x,y\right) &= \frac{2\mu_x\mu_y+C_1}{\mu_x^2+\mu_y^2+C_1}\ ;\ c\left(x,y\right) = \frac{2\sigma_x\sigma_y+C_2}{\sigma_x^2+\sigma_y^2+C_2}\ ; \\ s\left(x,y\right) &= \frac{\sigma_{xy}+C_3}{\sigma_x\sigma_y+C_3} \end{aligned} \tag{4}$$

with $C_i = (K_iL)^2$, $i \in \{1,2,3\}$ and L is dynamic range of pixel values. While $K_i \ll 1$ small constant. In practice, the mean SSIM index (MSSIM) is used to evaluate the overall image quality which is defined as follows:

$$MSSIM\left(X,Y\right) = \frac{1}{M}\sum_{j=1}^{M} SSIM\left(x_j,y_j\right) \tag{5}$$

4. Pratt's Figure Of Merit (Pratt's FOM) is a metric employed to assess and compare the ability of various noise reduction methods to preserve edges. The outcomes of Pratt's FOM are contingent on the specific edge detection technique utilized. In this study, the Canny edge detector was employed as the edge detection method. The formula for Pratt's FOM is articulated as follows:

$$FOM = \frac{1}{\max\left\{\hat{N},\ N_{ideal}\right\}}\sum_{i=1}^{\hat{N}}\frac{1}{1+d_i^2\alpha} \tag{6}$$

where $\hat{N}$ is number of edge pixels detected, N_{ideal} is ideal number of edge pixels, d_i is Euclidean distance between the ith detected pixel and the nearest ideal edge pixel, and α is a constant usually set to 1/9.

3 RESULT AND DISCUSSION

The initial experiment seeks to assess how the quality of the training images impacts the performance of noise reduction. The first image employed in this experiment is a phantom image, specifically

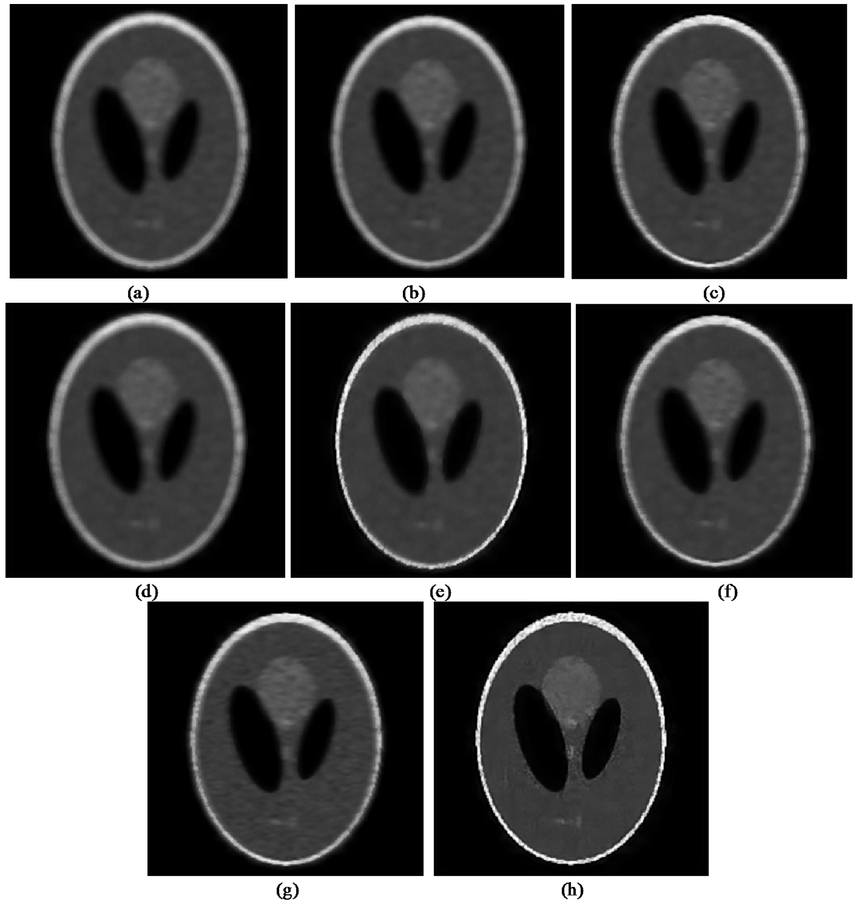

Figure 3: Results of reducing noise using the method (a) Lee filter, (b) Frost filter, (c) bilateral filter, (d) dual-tree wavelet transform, (e) SRAD, (f) hybrid speckle noise, (g) 9-layer without preprocessing and (h) DnCNN model without preprocessing.

a modified Shepp-Logan image, which was created using the phantom function in MATLAB and has dimensions of 200x200. Speckle noise is intentionally introduced into the phantom image, with a variability level of 0.1, and then processed using a network that has undergone training.

Table 1 compares preprocessing methods' performance to improve training data quality. The table shows that the best RMSE, 4.53, results from noise reduction using the Dual-Tree Wavelet (DTW) preprocessing method. Meanwhile, the best PSNR and MSSIM values, 26.78 and 0.92, respectively, were obtained using DnCNNs pre-trained networks and without preprocessing. However, the best Pratt's FOM value that shows the level of edge preservation was achieved with the hybrid speckle noise reduction preprocessing method, amounting to 91.76%. All networks trained without preprocessing, whether using 9-layer or 59-layer networks, have lower Pratt's FOM values, namely 79.39 and 79.58, respectively. Although DnCNN shows the best PSNR and MSSIM performance. This proves that the preprocessing stage has a significant influence in improving speckle noise reduction performance. Visually, a comparison of the speckle noise reduction results can be seen in Figure 3.

In the second experiment, the trained tissue was tested on 3D ultrasound images with varying sizes and numbers of slices, as explained in Subchapter 2.1. We compared the elapsed time between the 9-layer and DnCNN networks (59 layers). Table 2 shows a time comparison of the two types of networks for 3D images with image slice numbers 26, 53, and 320. This shows that for 3D images, the number of layers greatly influences the computing time.

4 CONCLUSION

The comparison parameters highlighted in the experiment underscore crucial aspects of deep speckle noise reduction. The evaluation in the first dataset highlights the Dual-Tree Wavelet (DTW) method's capacity, yielding the most favorable RMSE. The hybrid speckle noise reduction preprocessing method stands out for its paramount achievement in edge preservation, boasting a Pratt's FOM value of 91.76%. Interestingly, regardless of their layer count, networks trained without preprocessing exhibit inferior Pratt's FOM values despite DnCNN exhibiting better PSNR and MSSIM performance. These findings emphasize the significant impact of preprocessing on enhancing the efficacy of speckle noise reduction techniques. Moreover, the second test comparison underscores the

Table 1: Noise Reduction Performance Comparison

Preprocessing	CNN Layer	**RMSE**	**PSNR**	**MSSIM**	**Pratt's FOM**
Lee Filter	9 layers	28.037	19.21	0.78	88.32
Frost Filter	9 layers	27.024	19.53	0.80	87.73
Bilateral Filter	9 layers	23.48	20.75	0.83	91.16
SRAD	9 layers	16.19	23.98	0.89	89.58
DTW	9 layers	**4.53**	19.02	0.78	87.25
Hybrid Speckle Noise Reduction [3]	9 layers	23.68	20.68	0.83	**91.76**
Without Preprocessing	9 layers	21.53	21.51	0.84	79.39
Without Preprocessing	59 layers (DnCNN)	11.72	**26.78**	**0.92**	79.58

Table 2: Elapse Time Comparison For 3D Image Denoising

CNN Layer	**26 slices**	**53 slices**	**320 slices**
9 layers	13.264714 seconds	35.406203 seconds	88.006831 seconds
59 layers (DnCNN)	80.287093 seconds	214.552995 seconds	670.675970 seconds

importance of network architecture, particularly the layer count, in computing time for 3D images. The comparison between the 9-layer and 59-layer DnCNN networks reveals a distinct influence of layer count on processing efficiency for 3D images with varying slice numbers. These outcomes highlight the pivotal role of preprocessing methods and network architecture in achieving effective deep speckle noise reduction. Their success in enhancing edge preservation and reducing noise in ultrasound images indicates their potential for substantially improving diagnostic image quality in medical applications. In future research, developing a network that combines traditional denoising algorithms directly to simplify the process is necessary.

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