Journal of Digital Imaging (2020) 33:273–285
https://doi.org/10.1007/s10278-019-00211-5

Feature Enhancement in Medical Ultrasound Videos Using Contrast-Limited Adaptive Histogram Equalization

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Published online: 3 July 2019

Abstract
Speckle noise reduction algorithms are extensively used in the field of ultrasound image analysis with the aim of improving image quality and diagnostic accuracy. However, significant speckle filtering induces blurring, and this requires the enhancement of features and fine details. We propose a novel framework for both multiplicative noise suppression and robust contrast enhancement and demonstrate its effectiveness using a wide range of clinical ultrasound scans. Our approach to noise suppression uses a novel algorithm based on a convolutional neural network that is first trained on synthetically modeled ultrasound images and then applied on real ultrasound videos. The feature improvement stage uses an improved contrast-limited adaptive histogram equalization (CLAHE) method for enhancing texture features, contrast, resolvable details, and image structures to which the human visual system is sensitive in ultrasound video frames. The proposed CLAHE algorithm also considers an automatic system for evaluating the grid size using entropy, and three different target distribution functions (uniform, Rayleigh, and exponential), and interpolation techniques (B-spline, cubic, and Lanczos-3). An extensive comparative study has been performed to find the most suitable distribution and interpolation techniques and also the optimal clip limit for ultrasound video feature enhancement after speckle suppression. Subjective assessments by four radiologists and experimental validation using three quality metrics clearly indicate that the proposed framework generates superior performance compared with other well-established methods. The processing pipeline reduces speckle effectively while preserving essential information and enhancing the overall visual quality and therefore could find immediate applications in real-time ultrasound video segmentation and classification algorithms.

Keywords Ultrasound feature enhancement · Ultrasound despeckling · Contrast-limited adaptive histogram equalization · Image entropy · Image quality analysis

Introduction

Ultrasound imaging is the preferred diagnostic scanning technique for identifying abnormalities in human organs and tissues as it is generally easily available, non-invasive, and free of any type of harmful radiations [1]. However, ultrasound images have very low contrast and are corrupted by speckle noise. Most ultrasound image processing and analysis algorithms therefore focus on reducing speckle content, enhancing features for better structure visibility and improved clinical interpretation, and segmenting clinically relevant features such as lesions, tumors, and calcification [2–6].

Speckle artifacts affect the contrast and clarity of fine details and edges making it difficult to detect small and low-contrast anatomical features in the human body [7, 8]. As speckle reduction is performed on ultrasound images, it induces blurring which is again an important factor to consider when evaluating the quality of the processed images. As the distribution of speckle content varies across frames of an ultrasound video sequence, processing several frames of a video sequence allows us to get a better characterization of speckle noise present in the images. The

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image contrast also varies in consecutive frames depending on the physical movement of anatomical parts and the acquisition model used. Several studies have been reported over the recent past for the filtering of Gaussian additive noise from natural video sequences [9, 10], but not much work has been addressed on real medical ultrasound video despeckling. A research group [11–13] has performed an extensive comparative analysis of various well-established filtering techniques for ultrasound video frame processing using scans of common carotid arteries (CCA). Their study focused on only one kind of ultrasound video sequence and did not consider feature enhancement after the despeckling stage. It is important to include a feature enhancement step, as filtering may induce blurring of certain features in output frames that are clinically relevant. The main contribution of our study is that it has used videos of several anatomical structures for proving the efficacy of the developed methods. A speckle reduction filter for ultrasound video communication system was also proposed in [14]. This study has shown the potential of the despeckling filter prior to the compression and transmission of ultrasound videos, without compromising the clinical quality. They have compared three well-established filtering techniques that are linear, median, and speckle reducing anisotropic diffusion filtering and demonstrated that linear filtering is a suitable approach for the presented application. In [15], a fast spatial and spatiotemporal filtering method for multiplicative noise suppression was proposed specifically for ultrasound images and videos. Our work extends the process of despeckling with the addition of a feature enhancement step.

The main contribution of our work in the area of speckle filtering is that it proves the feasibility and effectiveness of using powerful convolutional neural network–based speckle removal techniques that have been previously used in the field of synthetic aperture radar imaging system [16]. In order to adopt the above technique to the domain of ultrasound video analysis, we use a completely novel approach of training the network using both noise-free and noisy versions of synthetically modeled ultrasound images, and applying the trained network on real ultrasound image frames. Extensive quality analysis of synthetic images has been carried out to ensure that their intensity and texture characteristics match with real ultrasound images, to justify their use in the training phase. The feasibility of the above approach was further verified by subjective evaluation of the quality of the speckle-reduced real ultrasound frames.

Histogram equalization methods [17] have been widely used in the field of image processing for improving both contrast and structure visibility. These methods make use of the overall intensity distribution in the image as characterized by the normalized cumulative histogram. Ultrasound images generally have a skewed histogram due to the presence of large areas of low intensity, and this results in a cumulative distribution function that maps a small intensity range to a very large area, and correspondingly non-uniform contrast stretching. Adaptive histogram equalization (AHE) methods try to overcome this problem by performing histogram equalization on small image tiles (contextual regions) [18]. These methods, however, do not work well with ultrasound images as they tend to amplify speckle noise present in homogeneous regions of the images. Contrast-limited adaptive histogram equalization (CLAHE) is a good contrast enhancement technique specifically for ultrasound images as they always contain speckle noise and low-intensity regions of very low contrast and resolvable details [19]. Several parameters of CLAHE affect the levels of feature enhancement in a given image frame. An important parameter is the tile size which has a direct impact on both computational complexity and output quality. Another important factor governing the outputs of the CLAHE algorithm is the distribution function that specifies the desired shape of the clipped histogram within each image tile. The clip limit specifies a threshold to which the histogram of an image tile is clipped to prevent over-amplification of noise and contrast in nearly uniform regions. The CLAHE also uses an interpolation algorithm to compute the intensity value at a pixel using the transform functions of up to four neighboring tiles that are located closest to the pixel. CLAHE has been successfully used to enhance several types of medical images such as Computer Tomography, MR, and retinal images [20, 21]. To the authors' knowledge, no work has been previously reported on a detailed analysis of the CLAHE method for ultrasound video contrast enhancement, taking into the effects of parametric variations on the quality of the output. This paper proposes a quantitative algorithm for automatically finding the tile size and clip limit used by CLAHE, based on the randomness (entropy) of the input frames and the quality of the output images. Three different types of distribution functions, viz., uniform, Rayleigh, and exponential, and also three different interpolation techniques, viz., bilinear, cubic, and Lanczos-3 [22–24], are used in the experimental analysis to compare the quality of the generated contrast-enhanced ultrasound frames. The main contributions of this paper in feature enhancement using the CLAHE can be summarized as follows:

1. The paper shows that the performance of the CLAHE algorithm could be significantly improved by using a pre-processing phase for speckle noise removal.
2. The algorithm discussed in this paper uses ultrasound video sequences instead of single image frames for obtaining improved results in both speckle noise reduction and feature enhancement.
3. The optimal clip limit for the CLAHE algorithm is automatically determined using the quality metrics evaluated from output frames.
4. The size of the image tiles (contextual regions) is determined automatically using a global entropy function.
5. The paper looks at three different types of distribution functions for the shapes of the target histograms in image tiles and performs a comparative analysis.

6. The paper shows that the interpolation scheme used by the CLAHE algorithm also plays a vital role and gives a comparative analysis of the experimental results using three types of interpolation algorithms.

This paper is organized as follows: The "Introduction" section discusses the problems associated with and applications of ultrasound video/image analysis algorithms, and in particular, the CLAHE algorithm for feature enhancement, and outlines the important aspects of the proposed solution. The "Overview of the Proposed Framework" section gives an overview of the processing stages of the proposed framework for despeckling and feature enhancement of medical ultrasonography videos. The "Contrast-Limited Adaptive Histogram Equalization" section details the methodology and system model used for the proposed CLAHE method. The sections "Image Quality Measures" and "Comparative Analysis" present the quantitative evaluations and the results of the comparative analysis among various methods. "Discussion, Conclusion, and Future Work" section gives a summary of the work presented in the paper and outlines future directions.

Overview of the Proposed Framework

The two main stages of the proposed processing pipeline are a convolutional neural network (CNN) and a contrast-limited adaptive histogram equalization (CLAHE) method as shown in Fig.1.

The first stage filters speckle noise from input frames and feeds them to the second stage that uses CLAHE for feature enhancement. The CNN uses ultrasound videos converted into frames as input. This process uses three convolutional layers including a batch normalization layer (BN) in the network configuration as shown in Table 1. At the CNN initialization step, image features are mapped as values of a single gray-level channel along image rows and columns. The features learned in the first CNN layer (L1) followed by ReLU are mapped to the second CNN layer (L2) followed by a ReLU. The third layer (L3) includes CNN batch normalization (BN) followed by tanh activation function to obtain learned features from the second layer which is used to eliminate detected speckle noise by dividing original input frames by the estimated speckle region [16, 25]. The network architecture was trained on 600-gray-level (8 bit) synthetic ultrasound images of size 256×256 pixels. The synthetic images were produced using an ultrasound image formation modeling algorithm proposed in one of our recently published papers [26]. The modeling algorithm generates synthetic images that closely resemble the intensity and texture characteristics of real ultrasound images, and at the same time, allows us to add speckle noise in a controlled manner. For our analysis, the standard deviation of speckle content varied through a wide range of values, from $\sigma = 0.3$ to $\sigma = 5.0$. The performance of the network was evaluated by comparing the predicted noise-free images with the actual noise-free synthetic images by utilizing auto-correlation functions, before adopting the network for speckle suppression of real ultrasound scans. The implementation of the proposed CNN architecture was carried out using the *MatConNet* toolbox [27]. No pre-processing step was used for modifying the intensity values of input images. All of the experiments were conducted on a Windows machine with 3.40 GHz, 4 cores processor, 16GB RAM, and GeForce GTX 960 graphics card.

Table 1 CNN configuration for speckle removal

	Layer	Filter size	#Filters
L1	Conv + ReLU	$3 \times 3 \times 1$	64
L2	Conv + ReLU	$3 \times 3 \times 64$	64
L3	Conv + BN + tanh	$3 \times 3 \times 64$	1

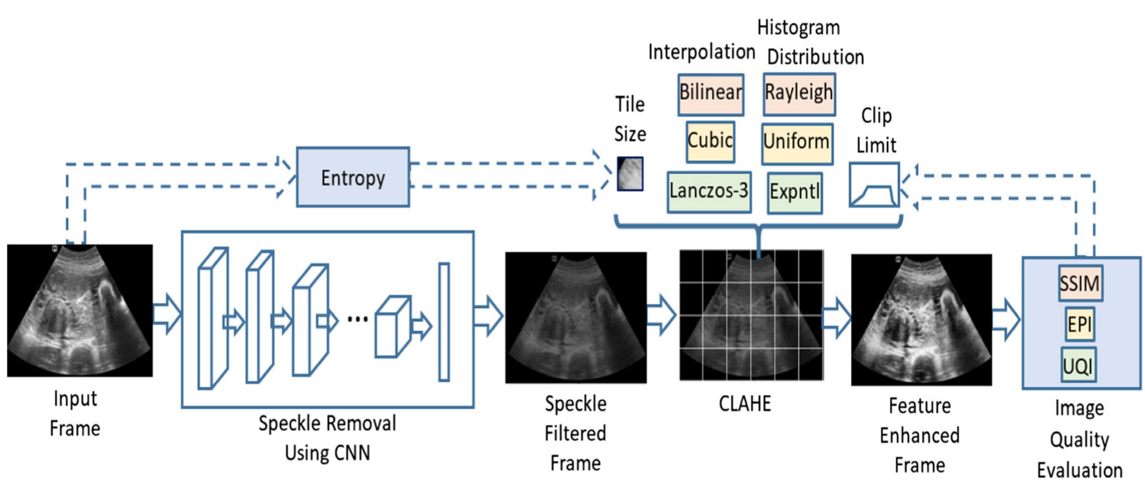

Fig. 1 The processing stages of the proposed pipeline for speckle reduction and feature enhancement

The real ultrasound video scans used in our analysis were obtained from www.ultrasound-images.com [28] with permission to use them in our research work. We have used six different types of video scans , i.e., breast cancer (480 × 640), uterine fibroids (312 × 460), transvaginal ovary (623 × 372), ovarian cyst (612 × 576), heart (532 × 432), and chest pleural effusion (640 × 480), each consisting 50 frames; all frames are of 8 bits, at the testing phase of trained model. After despeckling of ultrasound frames, we enhance features using the contrast-limited adaptive histogram equalization method which is the primary focus of this paper and discussed in the following sections.

The design of a two-stage processing pipeline as given in Fig. 1 is based on our experimental analysis of the CLAHE method that showed that it alone is not adequate for effective speckle filtering and enhancement. Figure 2 presents some results of contrast enhancement using the CLAHE based on Rayleigh distribution and Lanczos-3 interpolation to show why contrast enhancement is not recommended before speckle filtering. The output images presented in the second column of Fig. 2 clearly indicate that the CLAHE method overemphasizes the contrast of features present in the image and also amplifies speckle noise. The proposed framework performs speckle filtering followed by selective feature enhancement on local regions to improve the overall contrast and to eliminate the blurring problem in ultrasound videos. Experimental results using this approach and quality evaluations showing its effectiveness are presented in detail in the later sections of this paper.

Contrast-Limited Adaptive Histogram Equalization

The CLAHE method subdivides the image into a number of tiles. We estimate the tile size s using the global entropy of the input frame. For a greyscale image with 256 gray levels, the entropy E is defined as.

$$E = -\sum_{k=0}^{255} p_k \log_2(p_k) \quad (1)$$

where p_k is the probability associated with gray level k. We use an exponential decay function of the type

$$s = (M - E_{\max})\, e^{-\lambda E} + E_{\max} \quad (2)$$

to compute the tile size s based on the entropy value E for a given image of size M. The maximum entropy $E_{\max}$ for gray-level images is 8. The graph in Fig. 3, generated for the input image size $M = 256$ pixels and $\lambda = 0.7$, shows an example of the variation of tile sizes with entropy. When the entropy is in the maximum, the function gives a tile size of 8 × 8 pixels. For a very small entropy value 1 corresponding to a nearly uniform intensity distribution, we obtain a tile size that is half the size of the input image. Most ultrasound images have an entropy value within the shaded region of the graph in Fig. 3, where the tile size ranges from 8 × 8 pixels to 16 × 16 pixels.

We used three different types of target histogram distribution functions and three types of interpolations of transformation functions to analyze the performance of the CLAHE algorithm

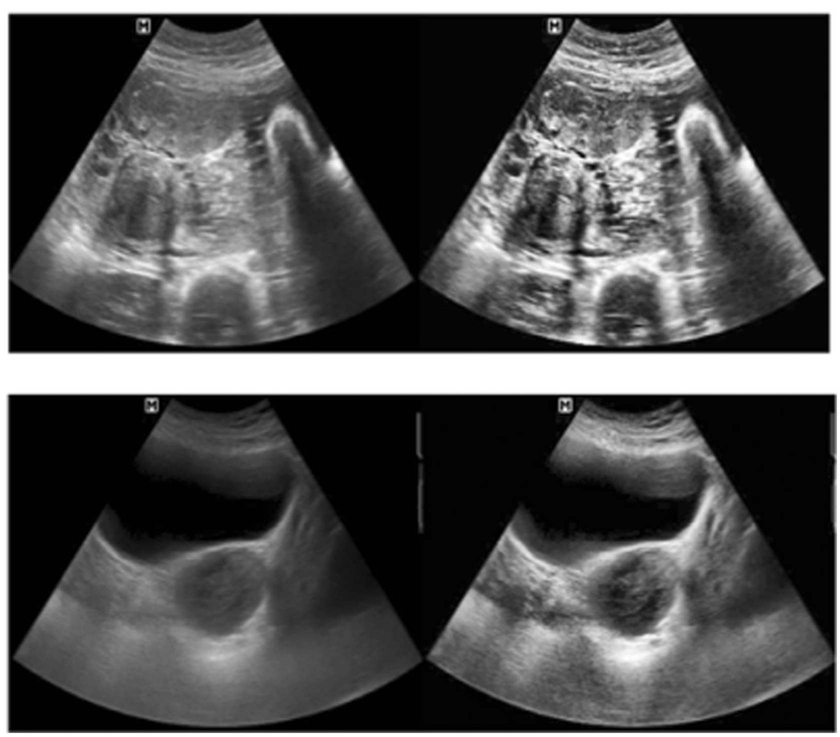

Fig. 2 Examples of original input ultrasound video frames (first column) and contract enhanced frame before speckle filtering (second column)

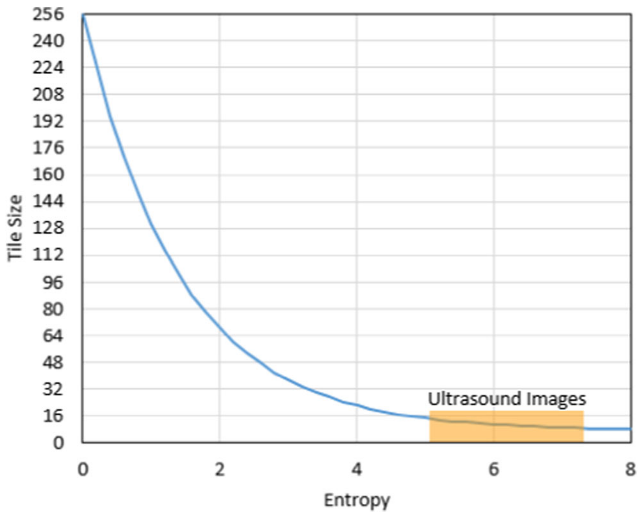

Fig. 3 A sample graph showing the variation of tile size with the entropy of the input image

on ultrasound videos. The distribution function specifies the shape of the target histogram of the contrast-enhanced image within each tile. Finally, the transform functions of neighboring small regions are combined using interpolation to eliminate any kind of induced artifacts [29, 30]. This paper considers three different types of distribution functions that are uniform, Rayleigh, and exponential. The conventional method of the CLAHE uses bilinear interpolation techniques for combining the transformation functions computed for neighboring regions. In our approach, we use three different interpolation systems, viz., bilinear, cubic, and Lanczos-3, individually to perform an extensive comparative analysis. The main aim of this evaluation is to find the best suitable combination for enhancing the contrast of ultrasound images/videos. The computational steps in the CLAHE method are listed below.

Processing steps in the CLAHE algorithm

1. Read the CNN-filtered image frame.
2. Divide images into a number of contextual regions using tile size evaluated using Eq. (2).
1. For each sub-region, calculate the uniform, Rayleigh, and exponential distribution function individually to get the desired histogram shape.
2. For each sub-frame, compute the histogram and the highest peak value. Initialize the clip limit using quantitative measures of image quality.
3. For each gray level bin in the histogram, if histogram bin > clip limit level, then clip the histogram bin.
4. Compute the transformation functions for each tile and use the selected interpolation method to combine the transform functions to get the new intensity value at each pixel position.

The above steps result in the enhancement of fine details in ultrasound frames as shown in Figs. 5, 6, and 7 and also in the subsequent sections.

It is important to choose the right value for the clip limit so that the enhancement of features across all frames is consistent and acceptable. If the clip limit is too high, it will cause contrast variation to oversaturate or if too low, will lead to an image with a flat histogram. An initial clip limit value of 0.01 has been experimentally determined and used for all nine combinations and all types of videos for the ultrasound analysis. As seen in Fig. 4, when the clip limit is increased from 0.01, the overall quality of the images showed a reduction as measured by metrics such as the structural similarity index metric (SSIM) and universal quality index (UQI) presented in the "Image Quality Measures" section.

As seen in Fig. 4, the initial clip limit provides nearly unity value for the SSIM metric for all three distribution functions. Similar results were obtained with other quality metrics (EPI, UQI) and interpolation functions used in our experimental analysis. In Fig. 5, we provide the outputs generated using three different values of clip limits 0.02, 0.04, and 0.08, and we see that all three images have larger than the desired levels of contrast enhancement, in comparison with the output for clip limit value 0.01. The SSIM, EPI, and UQI values indicated in Fig. 5 also show that the overall quality of the images measured using their structure, edges, and visual information gradually reduce as the clip limit is increased.

In Fig. 6, the first column represents the original ultrasound input frames of six different anatomical structures. The second column shows the speckle-filtered output generated using three-layer convolutional neural network model. The third column shows the output of the CLAHE algorithm based on the Rayleigh distribution and Lanzczos-3 interpolation. The outputs obtained by the processing pipeline have improved features, contrast, and resolvable details. Further, the speckle content has been suppressed significantly, and blurring is also reduced. Thus, the processing pipeline has the capabilities to address speckle noise issues and also perform acceptable levels of feature enhancement. Figure 7 shows the results using the remaining two distributions in combination with Lanczos-3 interpolation.

Figure 7 shows a comparison of outputs obtained from the CLAHE method based on uniform and exponential distributions and Lanzcos-3 interpolation. The outputs generated by using uniform distribution provide improved results except for the chest pleural effusion frames. This analysis demonstrates that we need the right combination of the distribution function and interpolation technique for obtaining the desired levels of feature enhancement in ultrasound videos/images. Out of all three distribution functions used in this study (Figs. 6 and 7), Rayleigh distribution in combination with Lanczos-3 interpolation gave better results as compared with the uniform and exponential distribution functions. A comparative analysis using bilinear and cubic interpolations is given below.

From Fig. 8, it is clearly seen that the output frames generated by the bilinear interpolation with all three distribution functions provided contrast-enhanced results. However, according to subject matter experts, bilinear interpolation provided over-contrast-enhanced frames which are not found to

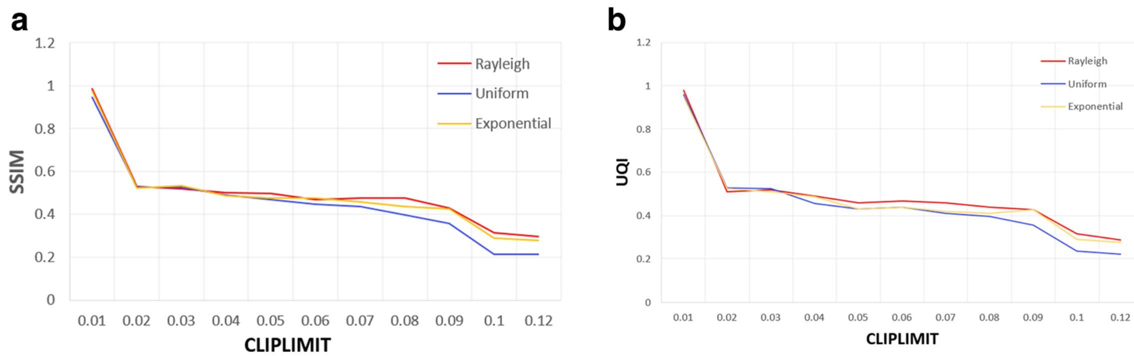

Fig. 4 Variations of output image quality as measured by SSIM (**a**) and UQI (**b**), with the clip limit used by the CLAHE algorithm for three different target distribution functions

be suitable for diagnostic analysis. As seen in Fig. 8, cubic interpolation (second column) generated relatively a lower degree of contrast enhancement. Among the distribution functions used with cubic interpolation, Rayleigh and exponential distribution functions gave better results.

Subjective Analysis of Ultrasound Videos

The framework for ultrasound video speckle reduction by CNN and feature enhancement using contrast-limited adaptive histogram equalization allows us to improve the overall visual quality of the video frames. It is important to perform a rigorous evaluation of the quality of the images to determine how feature enhancement after speckle filtering improves the diagnostic quality. In this section, the qualitative comparative analysis performed by four radiologists is denoted by R1, R2, R3, and R4 as provided in Table 2. The proposed work considered a wide range of human anatomical ultrasound video scans, i. e., breast cancer, uterine fibroids, transvaginal ovary, ovarian cyst, heart, and chest pleural effusion scan, to show the effectiveness of enhancement after filtering. In this subjective study, we have considered a total of 30 frames, 5 from each type of ultrasound scans. Nine combinations of each pair of input and output frames generated by the CLAHE system was reviewed randomly and independently by four subject matter experts and the mean scores for each of the six test cases are given on a five-point scale based on their subjective preference as shown in Table 2. The reviewers considered diverse image quality aspects during scrutiny of frames, such as the amount of speckle elimination, homogeneity, blurriness, structural information preservation, resolvable details, feature enhancement, and usefulness for the better diagnosis.

Table 2 indicates that the four subject matter experts who performed the evaluation have given a higher score to features improved by the CLAHE method when used in combination with Rayleigh distribution with Lanczos-3 interpolation. The outputs obtained using a combination of uniform distribution and bilinear interpolation were given the highest scores than other combinations of distribution functions and interpolation techniques. Those outputs do not show an over-amplification of contrasts of features. Besides subjective analysis, this paper gives equal importance to the quantitative evaluation of the output images in order to again validate the effectiveness of the chosen CLAHE combination (Rayleigh distribution and Lanczos-3 interpolation) and to compare with subjective evaluations.

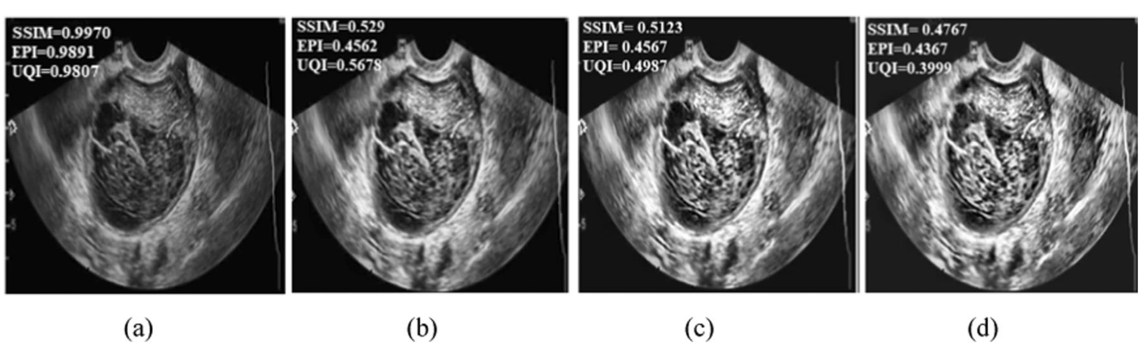

Fig. 5 Sample outputs showing the effect of variation of clip limit. 0.01 (**a**), 0.02 (**b**), 0.04 (**c**), and 0.08 (**d**)

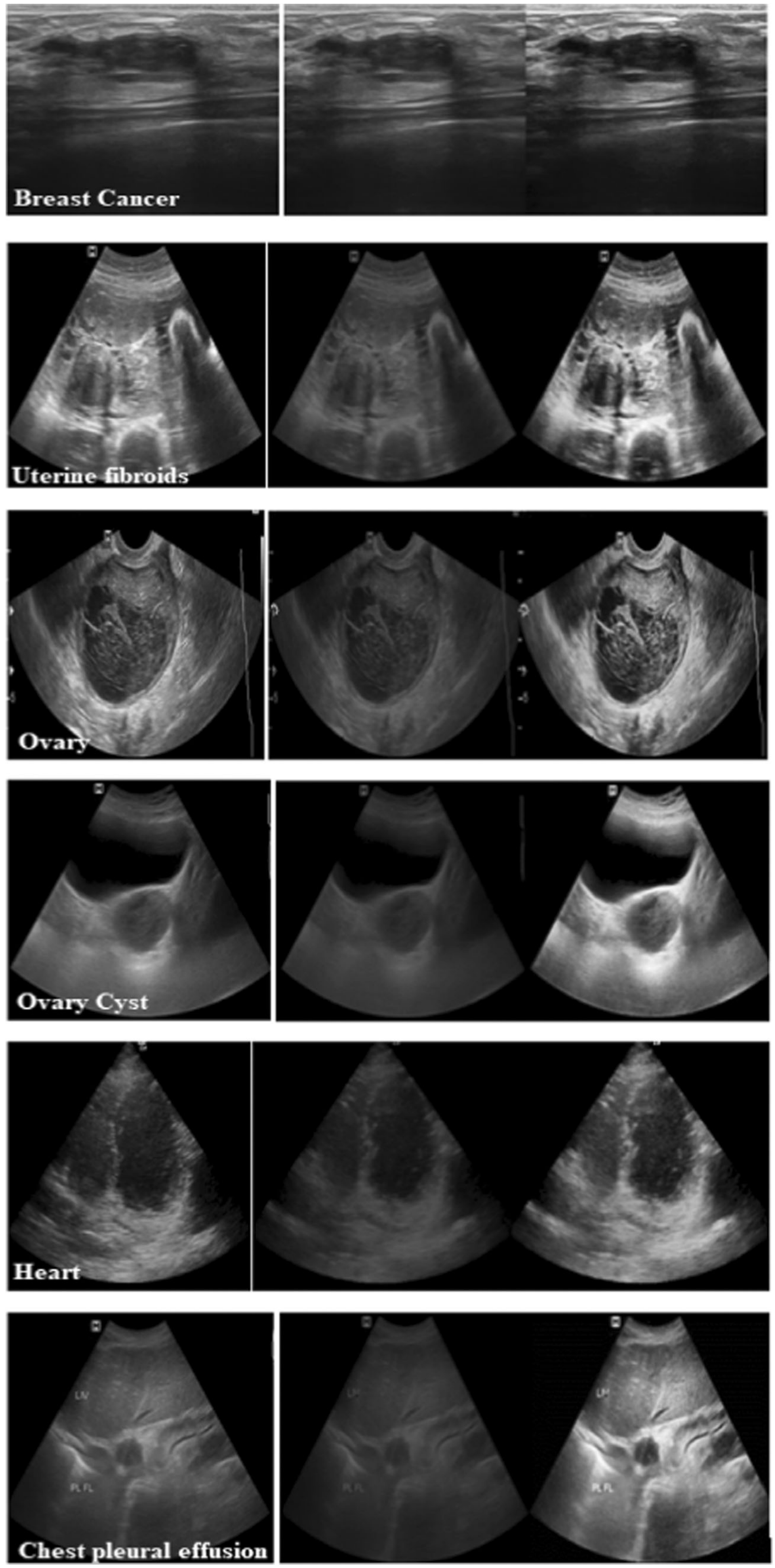

Fig. 6 Original ultrasound input frames (left side) before speckle filtering, speckle-filtered frames (center), and speckle-filtered feature enhanced frames using CLAHE with a combination of Rayleigh distribution and Lanczos-3 interpolation (right side)

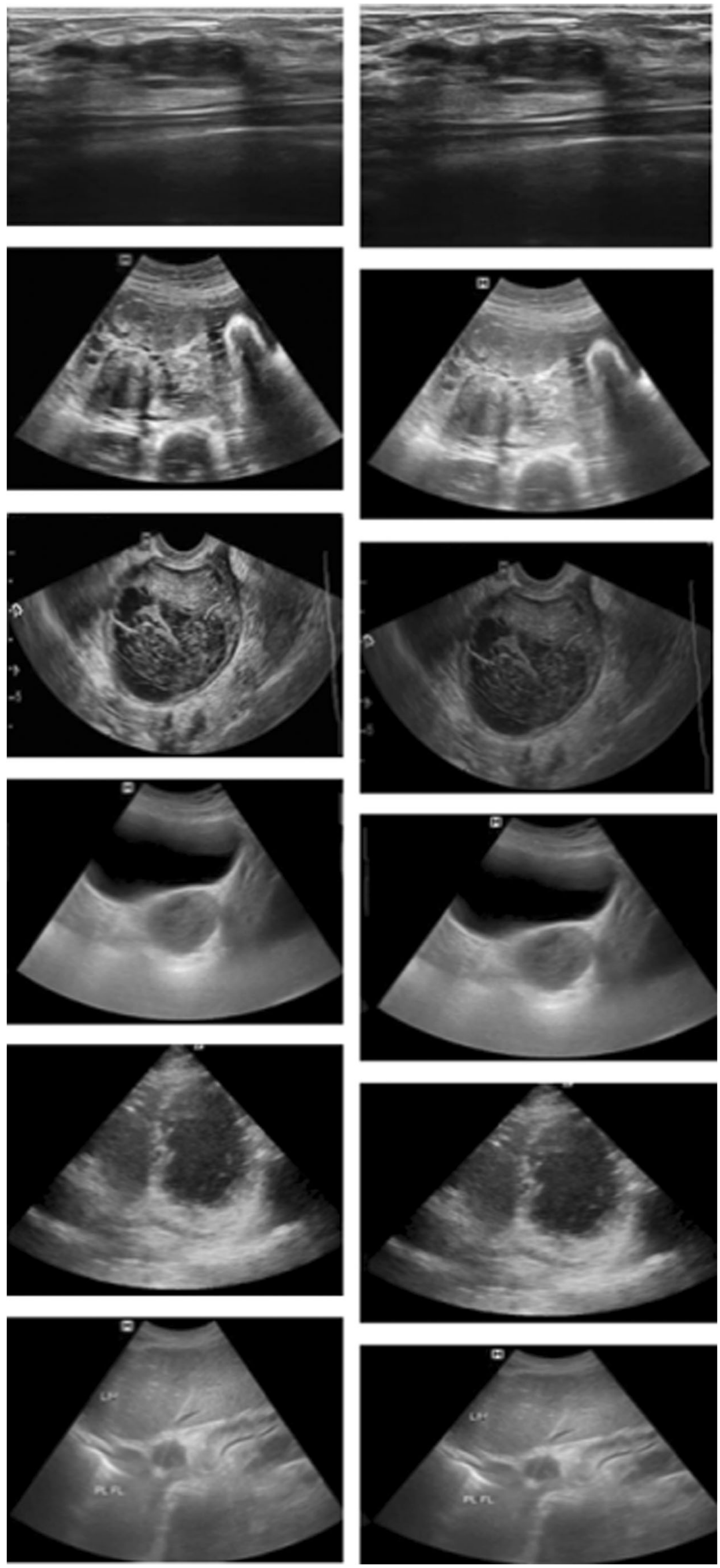

Fig. 7 Speckle-filtered feature enhanced ultrasound frames using CLAHE with a combination of uniform distribution and Lanczos-3 interpolation (left column) and exponential distribution and Lanczos-3 interpolation (right column)

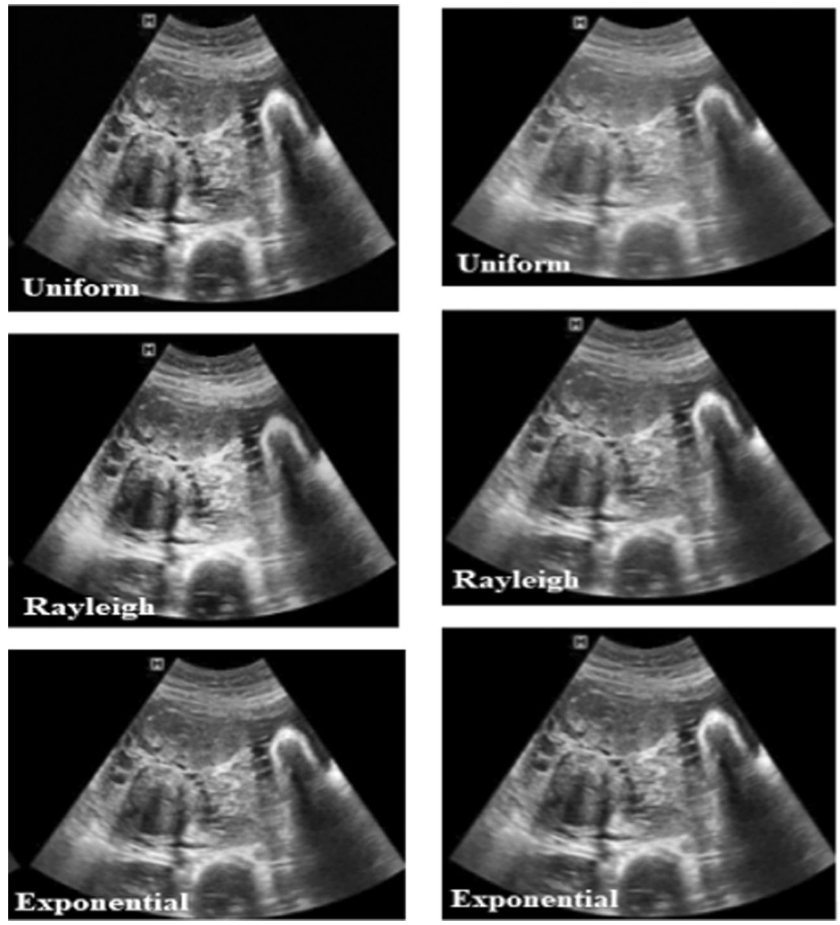

Fig. 8 Speckle-filtered feature enhanced ultrasound frames using the CLAHE algorithm using each of the three distribution functions. The first column shows the outputs with bilinear interpolation and the second column with cubic interpolation

Image Quality Measures

A complete analysis of interpolation and distribution functions used within CLAHE will help to select the best possible combination that improves the overall contrast and features of real ultrasound video frames. To evaluate the performance of the enhancement techniques, the quality of the feature-enhanced output frames are compared with input frames in terms of their capabilities in preserving the edge information, contrast, and structure details present in each ultrasound video frame. Here, we have considered three quality metrics that are structural similarity index (SSIM), edge preservation index (EPI), and universal quality index (UQI); the details of which are provided below [13]. In this analysis, we have used speckle-suppressed ultrasound video frames of uterine fibroids, the breast, and the ovary in order to perform a comparative assessment among three different types of the distribution functions and interpolation techniques. We have used 15 videos in each type of video scans and each video has 50 frames. Here, we have evaluated the quality metrics for the individual frames of each video and the mean value is presented in Tables 3, 4, and 5.

Table 2 Mean subjective evaluation score by four subject matter experts over six different kinds of ultrasound video datasets

Interpolation/ distribution	Uniform	Rayleigh	Exponential
Bilinear	4.75	4.5	4
Cubic	4	4.5	4.65
Lanczos-3	4	4.75	3.5

A. *Peak signal to noise ratio (PSNR)*

The peak signal to noise ratio measures how closely the filtered image resembles the original reference image. It is used to measure the quality of the filtered images and is measured in decibels.

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{v^2}{MSE}\right) \tag{3}$$

$$\mathrm{MSE} = \frac{1}{M \times N}\sum_{x=1}^{M}\sum_{y=1}^{N}\left(n_o(x,y) - n_r(x,y)\right)^2 \tag{4}$$

Table 3 SSIM for ultrasound video frames

Interpolation/ distribution	Uniform	Rayleigh	Exponential
Bilinear	0.9499	0.9799	0.9764
Cubic	0.8978	0.9256	0.9153
Lanczos-3	0.8965	0.9970	0.9467

where $n_o(x, y)$ and $n_r(x, y)$ are the output and reference images, MSE is the mean square error, and v is the maximum possible intensity value in the input image of size $M \times N$ pixels.

B. *Structural similarity index metric (SSIM)*

The structural similarity index metric is defined based on the human visual system (HVS). The SSIM between two images is given by

$$\mathrm{SSIM} = \frac{(2\mu_o\mu_r + 2.55)(\sigma_{or} + 7.65)}{({\mu_o}^2 + {\mu_r}^2 + 2.55)({\sigma_o}^2 + {\sigma_r}^2 + 7.65)} - 1 < \mathrm{SSIM} < 1 \quad (5)$$

where μ_o and μ_r are the mean of output image and reference image (or input image), respectively, σ_o and σ_r are the standard deviation of the output and reference images, and σ_{or} is the covariance.

C. *Edge preservation index (EPI)*

The EPI measure is used to ensure that the resultant image after CLAHE obtained through the proposed pipeline preserves edges. If the edges are preserved well during despeckling and enhancement processes, then EPI will have a value close to unity. The edge preservation index metric between two images is given as

$$\mathrm{EPI} = \frac{\sum_{x=1}^{M-1}\sum_{y=1}^{N-1}\left(\Delta n_r(x,y) - \Delta n_r{}'\right)\left(\Delta n_o(x,y) - \Delta n_o{}'\right)}{\sum_{x=1}^{M-1}\sum_{y=1}^{N-1}\left(\Delta n_r(x,y) - \Delta n_r{}'\right)^2\left(\Delta n_o(x,y) - \Delta n_o{}'\right)^2} \quad (6)$$

where $\Delta n_r(x, y)$ and $\Delta n_o(x, y)$ represent the edge images of reference image $n_r(x, y)$ and denoised output images $n_o(x, y)$. $\Delta n_r{}'$ and $\Delta n_o{}'$ are the mean intensities of Δn_r and Δn_o , respectively. $\Delta n_r(x, y)$ and $\Delta n_o(x, y)$ are the high-pass-filtered versions of images $n_r(x, y)$ and $n_o(x, y)$, obtained using a 3×3 pixel standard approximation of the Laplacian operator.

Table 4 EPI for ultrasound video frames

Interpolation/ Distribution	Uniform	Rayleigh	Exponential
Bilinear	0.9678	0.9567	0.8967
Cubic	0.8899	0.9467	0.9368
Lanczos-3	0.9596	0.9891	0.9738

Table 5 UQI for ultrasound video frames

Interpolation/ distribution	Uniform	Rayleigh	Exponential
Bilinear	0.9368	0.9568	0.9332
Cubic	0.9122	0.9467	0.9565
Lanczos-3	0.9669	0.9807	0.9567

D. *Universal quality index (UQI)*

Universal quality index is used to measure image distortions between two images by combining three factors: contrast distortions, luminance distortions, and loss of correlation. The UQI can be estimated using the equation given below.

$$UQI = \xi.\tau.c \quad -1 < UQI < 1$$
$$\xi = \frac{\sigma_{or}}{\sigma_o\sigma_r}, \tau = \frac{2\mu_0\mu_r}{{\mu_o}^2 + {\mu_r}^2}, c = \frac{2\sigma_o\sigma_r}{\sigma_o^2 + \sigma_r^2} \quad (7)$$

where ξ is the correlation coefficient that measures the correlation between original image and noise filtered image, τ measures the similarity of mean luminance between the two images, and c refers to contrast similarity of the images.

Tables 3, 4, and 5 give a comparative analysis of the objective quality assessments of the output images using all possible combinations of distribution and interpolation functions based on the three metrics presented above. In this paper, we have presented an analysis of nine combinations using three different distributions and interpolation techniques to find the best possible technique for the ultrasound video frame enhancement based on quantitative measures. All three image quality measures used in this study (SSIM, EPI, and UQI) yielded values close to unity when we compared speckle-reduced input images with the corresponding feature-enhanced output images. The speckle suppression by CNN and feature enhancement in ultrasound frames using CLAHE based on Rayleigh distribution and Lanczos-3 show better results for quality evaluation in terms of preserving structure and edges.

The subjective analysis and experimental demonstration using quality metrics together clearly show that the modified CLAHE using combination of Rayleigh distribution and Lanczos-3 interpolation with clip limit 0.01 and tile size obtained using the entropy measure provide impressive results by effectively reducing speckle noise, addressing the blurring issue, and enhancing the required features of ultrasound videos/images.

Comparative Analysis

In this section, we present a comparative analysis of the proposed method with various related state-of-the-art work in the

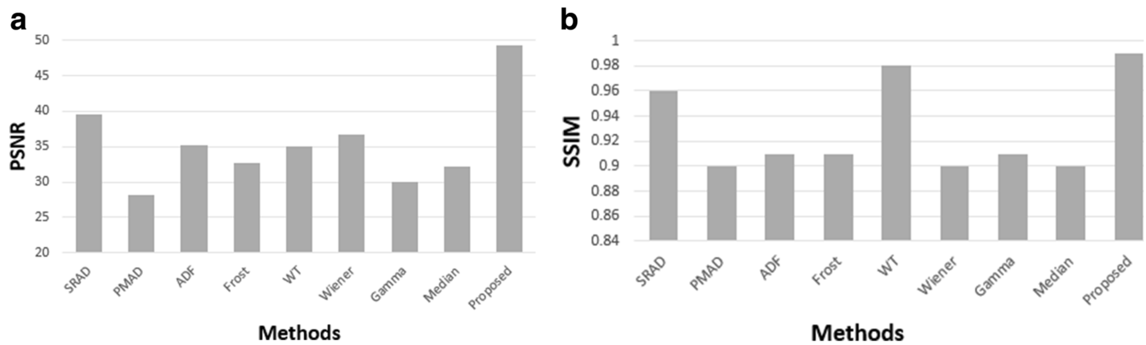

Fig. 9 PSNR and SSIM values for the outputs of the uterine fibroid scans

area of ultrasound video/image analysis. The idea to perform the comparative analysis with the filters mentioned below (Figs. 9 and 10) as most of the filters are used for the ultrasound video despeckling purposes so far in the literature review and speckle anisotropic diffusion filtering (SRAD) considered as the best approach among all filtering techniques developed so far for the speckle content suppression. Here, the despeckling and CLAHE feature enhancement using a combination of Rayleigh distribution and Lanczos-3 interpolation method compared with speckle-reducing anisotropic diffusion filtering (SRAD), Perona and Malik anisotropic diffusion method (PMAD), ADF, Frost filtering, wavelet method (WT), Wiener filter, and Gamma MAP [12–14]. Here, we have considered two image quality metrics SSIM and PSNR, and the study was performed on real ultrasound video frames of uterine fibroids and breast mass scans with a resolution of 480 × 640 and 312 × 460 of 8 bits.

The main motivation for using well-established filtering techniques for comparative analysis is that these methods are frequently used for ultrasound post-processing image analysis. Figures 9 and 10 indicate that the proposed system has yielded significantly higher values for quality metrics compared with the well-established filtering techniques developed for the speckle suppression and feature preservation. The proposed system has the capability to reduce speckle significantly as shown by a PSNR value higher than 45 dB, and to preserve structural similarity as shown by a SSIM value near to unity. The SRAD filter also showed better results compared with the other filtering techniques used in this study. Wavelet filtering also demonstrated good and comparable results to the proposed system in terms of preserving the structural content of the output frames as SSIM value is found to be sufficiently high.

The asymptomatic computational complexity is compared with the well-established filtering techniques mentioned in the "Comparative Analysis" section and presented in Fig. 11. The computational complexity is presented with respect to the size of frame used as input of the filtering methods. Figure 11a clearly indicates the time complexity is high for ADF and Wiener filter compared with the other methods used in the comparative analysis. The computational complexity of the proposed system is improved compared with the ADF, Wiener, and Gamma filters. The proposed system is taking more time compared with the SRAD, PMAD, and wavelet filters, since it has computationally complex stages for both filtering and feature enhancement. The PMAD has shown lower complexity compared with other methods; however, it generated images with comparatively lower visual quality (Figs. 9 and 10). The wavelet filter has also shown similar time complexity but noise reduction performance is not comparable with the SRAD and proposed method. Figure 11a shows that, in general, there is a trade-off between time complexity and visual quality of the processed images or videos. In terms of visual quality, time elapsed, and usefulness of the output images, SRAD and the proposed system performed well.

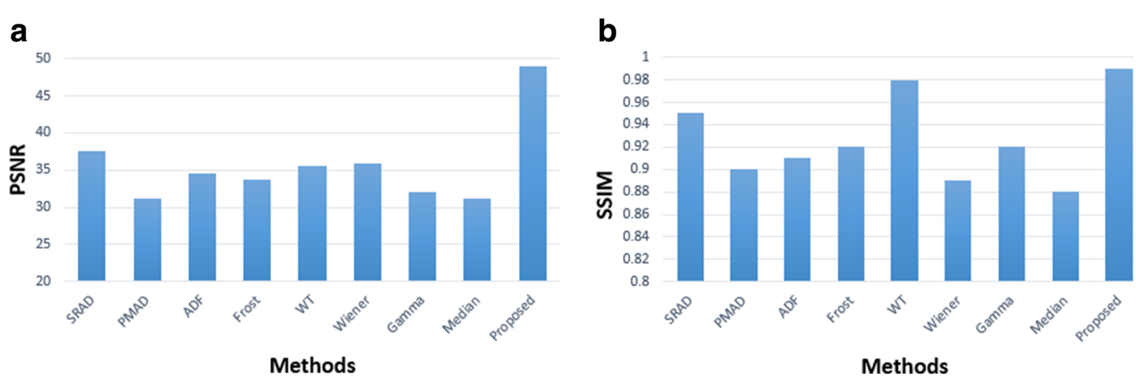

Fig. 10 PSNR and SSIM values for the outputs of the breast mass scans

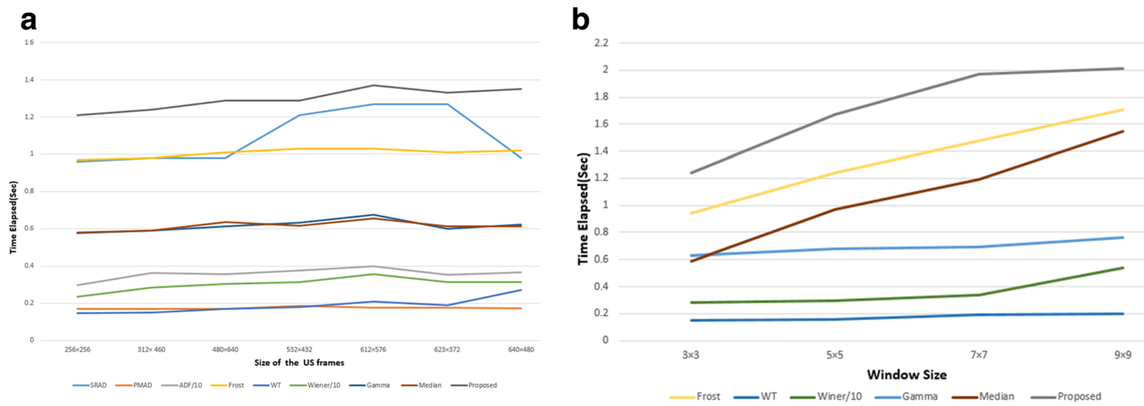

Fig. 11 Time complexity of varying frame size (**a**) and time complexity based on size of window (**b**) used for the filtering process

The analysis of computational complexity has been also presented with respect to variations in filter window size/mask size from 3 × 3 to 9 × 9, in Fig. 11b. For this comparative analysis, Frost, wavelet, Wiener, Gamma, and median filters are used to assess the effectiveness of the methods relative to the proposed system. The analysis shows that the time complexity varies approximately linearly with an increase in window size.

Discussion, Conclusion, and Future work

This paper has presented a complete framework for speckle noise removal and contrast enhancement of ultrasound videos. The primary design requirements were to minimize blurring caused by speckle filtering algorithms and to prevent overamplification of noise and contrast by feature enhancement algorithms. The processing pipeline used a novel CNN-based method for speckle noise removal and then the features were enhanced using an improved CLAHE algorithm. Three different types of distribution functions that are uniform, Rayleigh, and exponential were considered in combination with three different types of the interpolation techniques that are bilinear, cubic, and Lanczos-3, for comparative evaluation. The CLAHE method also utilized the entropy of the image to determine the number of contextual regions used in the subdivision step. The optimum clip limit was found using a quantitative analysis of the output image quality. The presented work has shown improved results compared with the other filtering methods in terms of the output image frame's visual quality and structural content preservation. The main limitation of the system is that it has more time cost compared with other filtering techniques (e.g., SRAD, PMAD, wavelet, and Frost) used in the study, being a sequential system that considered both despeckling and feature enhancement. The significant outcome of the system is that it provided sufficient speckle suppression with improved features as required for classification or segmentation algorithms.

In this research work, we have conducted an extensive quantitative analysis of the proposed algorithm using image quality metrics, and also qualitative evaluation by subject matter experts considering a wide range of image attributes to ascertain their usefulness in clinical applications. The experimental analysis conducted indicates CLAHE based on the Rayleigh distribution and Lanczos-3 interpolation technique improved features with the desired quality, for all types of ultrasound videos used in this study.

Future work is directed towards the development of a feature enhancement process within a filtering method to reduce computational complexity and improve overall efficiency. The proposed system could also be extended to an ultrasound video classification framework. For the classification of ultrasound videos, deep neural architecture will be considered and comparative study will be performed with other supervised learning techniques.

Acknowledgments We acknowledge the help extended by Dr. Khadijah Hajee Abdoula, Victoria Hospital; Quatre Bornes, Mauritius; Dr. Vivek Aggarwal, Thyroid Clinic, New Delhi, India; and Dr. Joe Antony, MD, India, in providing their expert advice, valuable inputs, and subjective evaluation of clinical post processed ultrasound images produced in this research. Dr. Joe Antony, MD, also provided the input of breast videos used in this research work [29].

Funding information This research work was supported by the College of Engineering Strategic Research Grant 2018, University of Canterbury.

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