Feature Enhancement in Medical Ultrasound Videos Using Multifractal and Adaptive Histogram Equalization Techniques

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***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 would require enhancement of features and fine details. In this paper, we consider the applications of multifractal features and contrast limit adaptive histogram equalization method for improving texture features, contrast, resolvable details, and image structures to which the human visual system is sensitive in ultrasound video frames. The experimental analysis considered various types of ultrasound video scans of the human anatomy e.g. breast cancer, uterine fibroids, transvaginal ovary, ovarian cyst, heart, and chest pleural effusion scan. Subjective assessments by four radiologists and experimental validation using three quality metrics clearly indicate that the proposed algorithm is able to reduce speckle effectively while preserving essential information and enhancing the overall visual quality.**

Keywords—Medical ultrasound video feature emhancement, Multifratals, Adaptive histogram equalization, Ultrasound video frames quality analysis .

I. INTRODUCTION

Ultrasound (US) imaging is widely used for clinical diagnosis owing to several desirable characteristics that minimize health risks such as non-invasiveness and absence of any form of ionizing radiation. This is the preferred technique for identifying abnormalities in human organs and tissues [1].
Ultrasound image processing and analysis find applicatons in several computer aided diagnostic systems [2]. These applications include enhancement of features for better clinical interpretations [3], image filtering for speckle noise reduction methods[4], and segmentation of clinically relevant features such as leisions, tumors, calcification etc. [5][6]. Ultrasound images can contain significant noise content especially speckle artifacts and Gaussian noise. Speckle artifacts are generated at all steps of image acquisition. There could be noise due to the loss of suitable interaction (or air gap) between the transducer and body, the beam forming process and the signal processing stage. Also, during scan conversion, there is loss of information due to interpolation. The techniques for ultrasound image filtering and analysis therefore concentrate on the reduction of speckle noise [7][8]. Speckle artifacts affect the fine details and edges which limit the contrast and resolution by making it difficult to detect small and low contrast clinical features in human body. As speckle reduction is performed in ultraosund scans, it induces blurring which is again an important factor to consider when evaluating the quality of the processed images. In this paper, we present a model which will perform desepckling, avoid blurring, and improve the contrast and fine details for effective clinical interpretation. To achieve the above stated goals, after despeckling of ulrasound vidoes, we considered two enhancement techniques that are contrast limit adaptive histogram equalization (*clahe*) and multifractal (*mfrac*) feature enhancement. Each technique has its own distinctive characteristics. The *clahe* is a good contrast enhancement technique for medical images specifically for ulrasound images where system generated ultrasound images are of very low contrast and have less resolvable details. On the other hand, multifractals can be be used for resolving local densities and are capable of handling irregularities present in the image. In this study, we have analysed the performance of each of the two techniques individually and also combinations of them for ultrasound scans.

The main contributions of our research work can be summarised as follows:

1. This work uses a convolutional neural network with medical ultrasound video frames as inputs to perform speckle filtering. Most of the work reported on speckle filtering use single image frames.
2. This work gives importance to both speckle reduction and feature enhancement. Adaptive histogram equalization and multifractal measures are used to enhance texture features and contrast. To the authors'

knowledge no work has been previously reported on the use of multifractal analysis for feature enhancement in medical US videos.

3. One of the main motivation of our research work is to show that a combination of adaptive histogram equalization and multifractals application to enhance both intensity based and local texture features simultaneously in ultrasound video frames.
4. Comparative analysis has been performed on the generated outputs by four subject matter experts (radiologists).
5. The paper has also presented a detailed quantitative evaluation of the outputs of the proposed algorithm using image quality metrics.

This paper is organized as follows: The next section gives an outline of the proposed framework/pipeline for despeckling and feature enhancement of medical ultrasonography videos. Section III and IV provides detail discussion of contract limit adaptive histogram equalization and multifractals. Section V and VI presents the subjective evaluation and the results of performance analysis using image quality metrics. Section VII gives a summary of the work presented in the paper and outlines future directions.

II. PROPOSED FRAMWORK

The main elements of the processing pipeline are a Convolutional Neural Network (CNN), adaptive histogram equalization step, and multifractal analysis as shown in Fig. 1. We use the proposed framework on a wide range of the ultrasound video scans for speckle reduction by CNN and feature improvement. Here, ultrasound (US) videos are converted into frames before they are processed through the proposed pipeline. In this process we have considered three convolutional layers including a batch normalization layer (BN) in the network configuration as shown in Table I.

Firstly, we perform CNN initialization, in which image features are mapped as image row, image column and image channel for each frame of US video. Then features learned in the first CNN layer (L1) followed by ReLU are mapped to second CNN layer (L2) followed by a ReLU. Here, in both the layers L1-L2 speckle artefact present in each frame is estimated using statistical features directly from the amplitude distribution and Nelder Mead optimization [9-10]. The third layer (L3) include CNN batch normalization (BN) followed by Tanh activation function to obtain learned features from second layer which is used to eliminate detected speckle noise by dividing original input frames by the estimated speckle region [11]. After despeckling of ultrasound frames, we enhance features to improve the diagnostic quality of the images using two types of feature enhancement techniques that are contrast limit adaptive histogram equalization and multifractal analysis. Each technique is applied independently and also in combination to compare their performance and also to show their effectiveness in the enhancement of the output obtained by CNN process. A detailed discussion of two feature improvement techniques have been provided in section III and section IV respectively, along with an analysis of the generated outputs.

Table I: CNN network configuration for speckle removal.

	Layer	Filter Size	#Filters	Output
L1	Conv+ReLU	3×3×1	64	480×640×64
L2	Conv+ReLU	3×3×64	64	480×640×64
L3	Conv+BN+Tanh	3×3×64	1	480×640×1

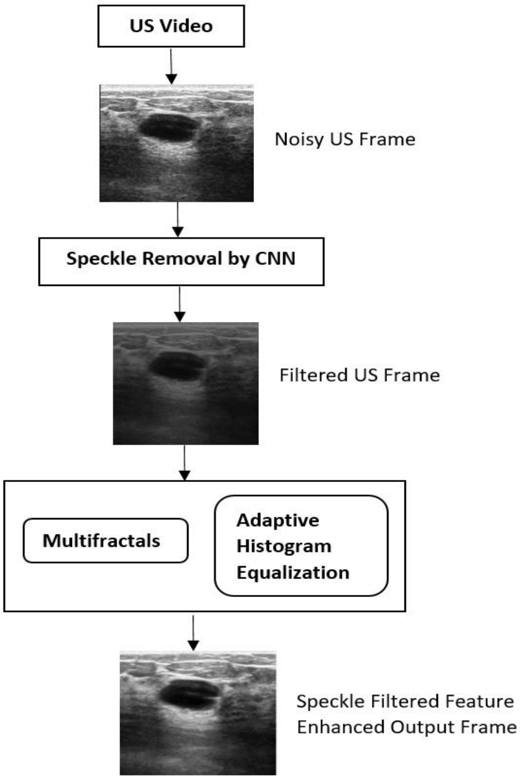

Fig.1.Medical ultrasound feature enhancement processing pipline.

III. CONTRAST LIMIT ADAPTIVE HISTOGRAM EQUALIZATION

Ultraosund videos generally consist of low contrast frames with bright and dark regions. We use a modified adative histogram equalization technique, which is contrast limit adaptive histogram equalization (*clahe*) [12] to improve contrast. The *clahe* operates on small regions rather than on the entire frame. Each tile of the particular US frames contrast or feature has been improved to approximately matches the Rayleigh distribution function. Finally, neighbouring small regions are combined using Lanczos-3 interpolation to eliminate any kind of induced artefacts. The steps given below are perfomed to attain the enhanced US frames by *clahe* method.

1. *Read each frame of the ultrasound video one by one.*

2. *Extract the grid regions based on the maximum size of the frames. Here, input frame into sub-regions of size 32×32 pixels.*
3. *For each sub-region calculate the Rayleigh distribution of the pixel intensities within it. For each sub-frame compute the histogram and the highest peak value. Determine the nominal clipping limit*[13].
4. *For each gray level bin in the histogram do the following:*
   (a) If histogram bin > nominal clip limit level, then clip the histogram.
   (b) Collect the number of pixels in the sub-frame that caused the histogram bin to exceed the clip limit.
5. *Conventional method of* ***clahe*** *uses bilinear interpolation techniques for combining the grid regions. In our approach, neighbouring regions are combined using Lanczos-3 interpolation to eliminate the artificially induced boundaries.*
6. *The above steps result in the enhancement of fine details in ultrasound frames as shown in the Fig.2 and the experimental sections V and VI.*

IV. MULTIFRACTALS FOR FEATURE ENHANCEMENT

Multifractal analysis is used in algorithms for image classification, pattern recognition, and segmentation where texture features are important [14]. It is also an effective and promising tool for enhancing medical images and extracting texture features [15]. However, it has not been used in ultrasonography images which contain speckle atrefact, bright and dark regions, fine structural details and complex image features. There are four commonly used intensity measures in the multifractal analysis: summation measure, maximum measure, inverse–minimum measure and iso measure [16]. In this work, we have used the inverse minimum measure which has performed well as compared to other three measures in enhancing the texture features of the speckle filtered US frames. A multifractal (*mfrac*) measure is denoted as $\mu_w(\rho)$, where ρ is the central pixel within a square window of size ω. Let $g\,(k,l)$ represent the intensity value of the pixel at the position of (k,l) inside the window, and Ω denote the set of all neighbourhood pixels of ρ in the window.

The first step in the computation of multifractal features is the estimation of the *Holder exponent* α [17]. The minimum intensity measure obeys an inverse power law and gives negative values of α. The computed minimum value is then inverted with respect to the maximum intensity value to get an inverse minimum measure that has the required scaling property.

$$\mu_{inv-min}(\rho) = 1.0 - \underset{(k,l)\in\Omega}{\mu_{min}}\, g(k,l) \qquad (1)$$

In Fig.2, the first column represents the original input frames of six different kinds of ultrasound video scans. The second column shows the speckle filtered output generated using three layer convolutional neural network model. Third column shows the output of the *clahe* algorithm. 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 capabilities to address speckle noise issues and also perform feature enhancement.

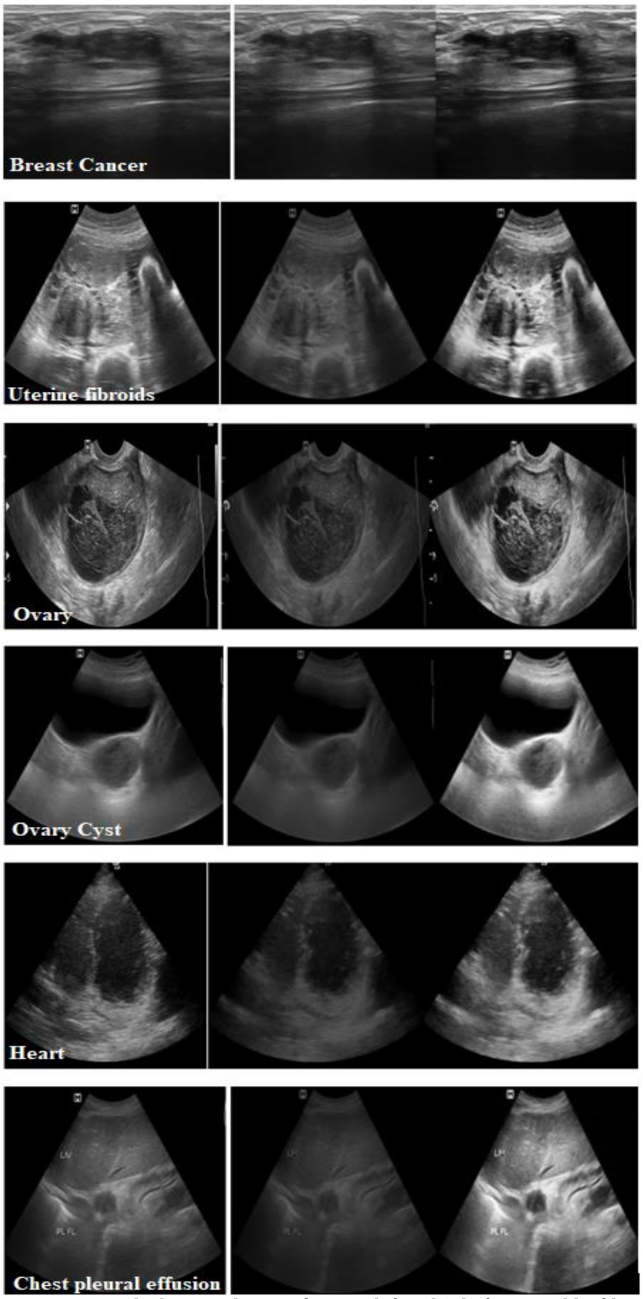

Fig. 2. Original ultrasound input frames (left side) before speckle filtering, speckle filtered US video frames (centre), and speckle filtered feature enhanced US frames using *clahe* (right side).

Fig.3 presents speckle suppressed frames in the first column, α-images in the middle, and feature enhanced using inverse-minimum measure of multifractals in the third column. We created α-images of the same size as the original by letting the intensity of each point in the α-image represent the Holder exponent at the corresponding point in the original images. For generating a α-slice, we select the pixels in the α-image belonging to a particular range of α values ($\alpha_{min}, \alpha_{max}$) and scaled their intensity values. Output feature enhanced images obtained by multifractals have shown improvement for some types of US scans like breast, heart but on the other hand in some images undesirable effects are induced. Because of space limitations, we have presented only a few types of US videos but the proposed framework shown in Fig.1 was used extensively on different types of ultrasonography video scans of human anatomical parts. As can be seen in column-2 of Fig 3, the multifractal decomposition of images into α-images is useful in characterizing various shape and texture features of anatomical structures present in the ultrasound images.

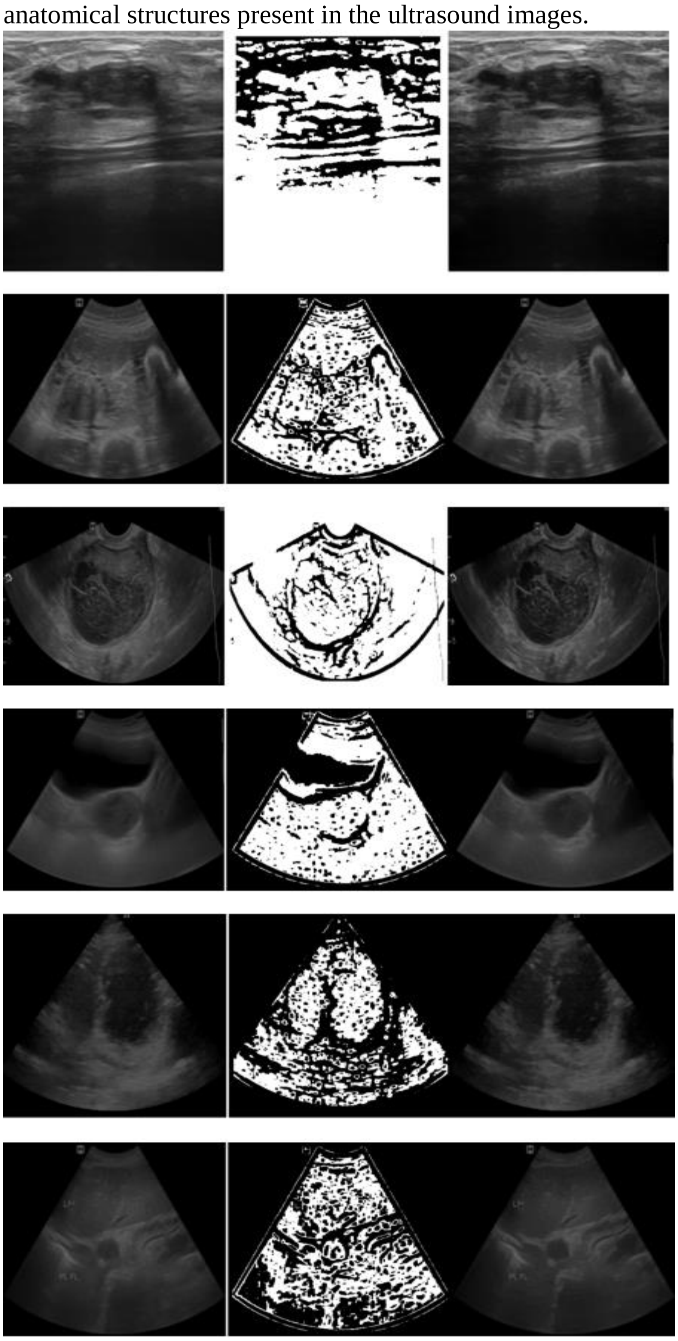

Fig. 3. Speckle filtered US video frames (left side), alpha images (α) of the multifractal (centre), enhanced US frames using multifractal measures (right side).

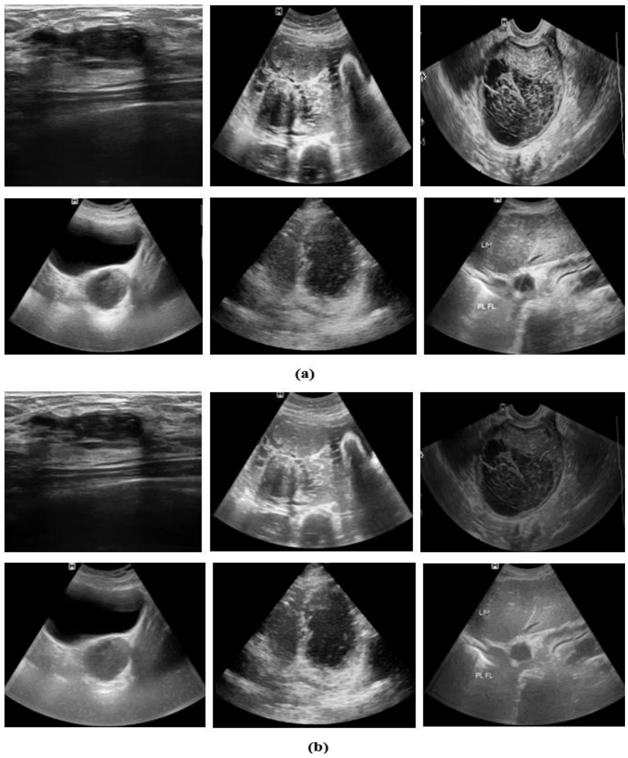

Fig. 4. Enhanced US video frames for the six test cases using a combination of *clahe, mfrac* methods performed in different sequences: (a) *clahe* followed by *mfrac* (b) *mfrac* followed by *clahe*.

Fig. 4 shows the enhancement of medical ultrasound video frames using a combination of *mfrac* and *clahe* techniques. In fig. 4(a), the ultrasound frames are first filtered using CNN architecture, then intensity based method used to improve the overall contrast of each US frames then local texture features are impoved using inverse min multifractal measure. In fig.4(b) same process has been used, but the order in which the *mfrac* and *clahe* methods are applied is reversed.

V. SUBJECTIVE ANALYSIS OF ULTRAOSUND FRAMES

The framework for ultrasound video speckle reduction by CNN and feature enhancement using contrast limit adaptive histogram equalization, and multifractal methods allows us to improve the overall visual quality of the images. It is important to perform a rigorous evaluation of quality of the images to determine how feature enhancement after speckle filtering improves the diagnostic quality. In this section qualitative comparative analysis performed by four radiologists are denoted by R1, R2, R3, and R4. The output of the two feature enhancement techniques used individually and in combination are used in this paper to perform the subjective evaluation. The proposed work considered wide range of human anatomical US video scans e.g. 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 total 30 frames 5 from each type of US scans. Each pair of input and output frames generated by the *clahe*, *mfrac*, and in combination of two techniques (*clahe+mfrac* and *mfrac+clahe*) was reviewed randomly and independently by four subject matter experts and the rounded off mean scores for each of the six test cases are given on a 5 point scale based on their subjective preference as shown in Table II. However, 5 score indicates overall quality of output frames are better than input frames, 4 score shows acceptable results, and 2 or below score indicates results are not good enough. The reviewers considered diverse image quality aspects which is valuable 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. Original, speckle removed and feature enhanced frames by *clahe* shown in Fig.2, and Fig.3 shows speckle removed images, α-images, and feature improved by inverse- minimum multifractal measure. Fig.4 shows the output of combination of two feature enhancement techniques. Table II indicates four subject matter experts has given 5 score to features improved by *clahe* and lesser scores to features enhanced by multifractals technique. Even though when two techniques are combined improved results are attained as compared to when inverse-min applied independently. As shown in uterine fibroids frames and chest pleural effusion images in the third column of Fig. 3, the *mfrac* method induced some kind of unwanted artifacts in the speckle removed frames. Both *clahe* and *clahe+mfrac* based image improvements are therefore preferred. However, *clahe+mfrac* considered both contract and local texture present in the frames.

Table II: Mean subjective evaluation by subject matter experts.

QM	*clahe*	*mfrac*	*mfrac+ clahe*	*clahe+ mfrac*
R1	5	4	4	4
R2	5	3	3	5
R3	4	3	4	5
R4	5	3	4	4

VI. Quality Measures (QM)

To evaluate the performance of the enhancement techniques, the quality of the feature enhanced output frames are compared with input frames in terms of the preserving the edge information, contrast, and structure details present in the each US video frames. Here, we have considered three quality metrics that are structural similarity index, edge preservation index, and universal quality metrics details are provided below. In this analysis we have considered ultrasound uterine fibroids and ovary video frames.

A. Structural Similarity Index Metric (ssim)

The ssim can be defined as a quality metric which is based on the human visual system (HVS). The *ssim* between two images is given by,

$$ssim = \frac{(2\mu_o\mu_r+2.55)(\sigma_{or}+7.65)}{(\mu_o{}^2+\mu_r{}^2+2.55)(\sigma_o{}^2+\sigma_r{}^2+7.65)} \qquad -1<ssim<1 \qquad (2)$$

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

B. Edge Preservation Index (epi)

To ensure that resultant image after denoising through proposed pipeline preserves edges, so we have used *epi*. If the edges are preserved well during despeckling process, then *epi* is close to unity. The Edge Preservation Index metric between two images is given as

$$epi = \frac{\sum_{x=1}^{M-1}\sum_{y=1}^{N-1}(\Delta n_r(x,y)-\Delta n_r{}')(\Delta n_o(x,y)-\Delta n_o{}')}{\sum_{x=1}^{M-1}\sum_{y=1}^{N-1}(\Delta n_r(x,y)-\Delta n_r{}')^2(\Delta n_o(x,y)-\Delta n_o{}')^2} \qquad (3)$$

where $\Delta n_r(x,y)$ and $\Delta n_o(x,y)$ represents the edge images of reference image $n_o(x,y)$ and denoised output images $n_r(x,y)$. $\Delta n_r{}'$ and $\Delta n_o{}'$ are mean intensities of Δn_r and Δn_o repectively. $\Delta n_r(x,y)$ 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 3×3 pixel standard approximation of the Laplacian operator.

C. Universal Quality Index (uqi)

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

$$uqi = \xi.\tau.c \qquad -1 < uqi < 1$$

$$\xi = \frac{\sigma_{or}}{\sigma_o\sigma_r}, \quad \tau = \frac{2\mu_o\mu_r}{\mu_o{}^2+\mu_r{}^2}, \quad c = \frac{2\sigma_o\sigma_r}{\sigma_o^2+\sigma_r^2} \qquad (4)$$

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.

Table III: Feature enhancement analysis in US video frames

QM	*clahe*	*mfrac*	*mfrac+ clahe*	*clahe+ mfrac*
ssim	0.9970	0.7631	0.7056	0.7759
epi	0.9891	0.8438	0.8323	0.8796
uqi	0.9807	0.8390	0.9489	0.9682

Table III presented structural details and edge preservation, and measures distortion between the two images of US fames after passing through the proposed pipeline in Fig 1 and feature enhanced using *clahe* and *mfrac*. All three image quality measures used in this study that are ssim, epi, and uqi are closer to unity in the case of *clahe*. After *clahe* the combination of *clahe+mfrac* performed quite well. It shows after speckle suppression by CNN and feature enhancement in ultrasound frames using *clahe* and *clahe+ mfrac* show better results in terms of structure and edge preservation, negligible distortion in terms of contrast, luminance, and correlation loss of two images (speckle reduced input and feature enhanced output) as compared to the output images obtained from the *mfrac* and *mfrac+clahe* methods.

The subjective analysis and experimental demonstration provides clear intuition that both *clahe* and *clahe + mfrac* combination contribute to improved results. The *clahe + mfrac* technique appears to be a better option as it provides feature enhancement using both intensity and local features. Also, the *clahe+mfrac* combination has addressed the issue of over contrast enhancement.

VII. Conclusions and Future Work

This paper has proposed a speckle suppression and feature enhancement framework for ultrasound video scans. This paper has given importance to reducing blurring which is an effect of the speckle filtering in ultrasound videos or the images. Here, we have used two feature enhancement techniques independently and in combination that are contrast limit adaptive histogram equalization and multifractals. In this work more importance has given to the quantitative evaluation the set of frames from the different types of ultrasound video evaluated by subject matter experts. Radiologists have considered wide range of visible features which is atmost important for the diagnostic reasoning. The experimental analysis conducted indicates *clahe* and after that *clahe +mfrac* provide improved features for all types of video frames than inverse min multifractal analysis. Here, we have also used three quality metrics that are *ssim*, *epi* and *uqi* to determine the structure detail and edge preservation, distortion in terms of contrast, luminance, and loss of correlation in the output frames after feature enhancement.

Future work will be directed towards the development of the ultrasound video classification system by using pre-processed medical ultrasound video using proposed framework in this paper. For the classification for the videos deep neural architecture will be considered and comparative study will be performed with other supervised learning techniques.

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