Speckle Reduction in Medical Ultrasound Imaging based on Visual Perception Model

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***Abstract*—Ultrasound imaging technology is one of the most important clinical imaging modalities due to its safety, low cost, in addition to its versatile applications. The main technical problem in this technology is its noisy appearance due to the presence of speckle, which makes reading imaging more difficult. In this study, a new method of speckle reduction in medical ultrasound images is proposed based on adaptive shifting of the contrast sensitivity function of human vision using a bias field map estimated from the original image. The aim of this work is to have an effective image enhancement strategy that reduces speckle while preserving diagnostically useful image features and allowing practical implementation in real-time for medical ultrasound imaging applications. The new method is used to improve the visual perception of image quality of ultrasound images by adding a local brightness bias to the areas with speckle noise. This allows the variations in image pixels due to speckle noise to be better perceived by the human observer because of the visual perception model. The performance of the proposed method is objectively assessed using quantitative image quality metrics and compared to previous methods. Furthermore, given that image quality perception is subjective, the level of added bias is controlled by a single parameter that accommodates the different needs for different users and applications. This method has potential to offer better viewing conditions of ultrasound images, which translates to higher diagnostic accuracy.**

Keywords*—*Contrast sensitivity function; image quality metrics; speckle reduction; ultrasound imaging

I. INTRODUCTION

Ultrasound imaging technology is one of the most important clinical imaging modalities due to its safety, low cost, in addition to its versatile soft tissue imaging applications that include abdominal imaging, echocardiography, and obstetrics and gynaecology [1]. Given that this technology relies on sending low intensity acoustic waves into the body and receiving the reflected and scattered echoes to reconstruct a cross sectional image of the body, it is inherently safe and can be considered as the safest imaging modality available today. This is evident by being the only imaging modality allowed for use on pregnant women to follow up the growth of the fetus and assess its biophysical profile in addition to detecting any anomalies present. Another advantage of ultrasound imaging technology is its availability in a wide range of forms including basic hand-held or portable units that cost a few thousand dollars to sophisticated dedicated echocardiography systems that cost hundreds of thousands of dollars. This allows ultrasound imaging to be popular for use in rural and low-income communities as well as in large, specialized hospitals. Future direction in this technology indicates that it will likely become as essential to medical practice as the stethoscope and it is predicted that general practitioners will soon have small ultrasound units in their clinical practice.

Despite the many advantages of ultrasound imaging technology, it has a clear shortcoming in the quality of its image as compared to other modalities such as x-rays, magnetic resonance imaging or computed tomography. Ultrasound images generally look very noisy to the viewer and requires some training to correlate the anatomy to the acquired ultrasound images. This is mainly due to the presence of speckle that sometimes obscure pathological changes in the body and hence may cause errors in the diagnosis. Therefore, the problem of speckle reduction in ultrasound images has been the focus of research of many academic and industrial research groups since the early beginnings of ultrasound imaging and is expected to remain so given its impact on this technology [2].

Speckle noise is an unavoidable direct result of the physics of ultrasound imaging. Ultrasound imaging is done by sending an ultrasonic pulse through the body from an ultrasonic transducer arranged in 1D or 2D array form. This ultrasonic pulse propagates through the tissues and interact with its different components yielding reflected waves from specular reflectors and scattering from point reflectors [1]. The difference between specular and point reflectors is mainly in size whereas specular reflectors are larger than the wavelength of ultrasound waves while scatterers are significantly smaller than this wavelength. This wavelength is a fraction of a millimeter in the usual range of ultrasound imaging frequencies in the 2-15 MHz. Therefore, tissue interfaces and major blood vessels behave like specular reflectors while blood capillaries and cells within the extracellular space act as scatterers [3][4]. So, in a tissue like the liver, hepatocytes scatter ultrasound waves independently and the backscattered part is what is received by the ultrasound transducer. Given that such scattering depends on the ultrasound transducer frequency and orientation as well as the complex 3D structure of the tissue, the received scattered waves from the many cells involved interfere and produce a pattern of partial constructive and destructive interference points that show as random noise in the image. The difference between speckle noise and true random noise is that random noise change with time and hence can be reduced by simple averaging. On the other hand, speckle noise pattern remains the same as long as the imaging

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conditions remain the same (i.e., probe orientation, frequency, and tissue being imaged). Therefore, it does not improve with averaging and other more sophisticated methods much be utilized to reduce its effect on image quality [5][6].

II. Literature Review

Several approaches have been proposed to address the problem of speckle reduction. Such approaches can be broadly classified as acquisition and post-processing methods. The acquisition methods try to reduce speckle through the acquisition of multiple versions of the same slice with each acquired with different beamforming (e.g., using steering, different focal point, different frequency, etc.). Then, since the speckle pattern is different when beamforming changes, using simple averaging of these acquisitions will result in an image with reduced speckle [1][7][8]. Despite the intuitiveness of the approach and apparent simplicity, it practically requires reprogramming of the acquisition protocols of different applications, which adds significant cost in addition to being a cumbersome constraint in some applications that require high frame rate and/or special ordering of acquisitions such as in 3D and 4D imaging.

On the other hand, the second approach based on preprocessing was the focus of virtually all research groups working on this problem since the 1980s until today. Its basic premise is to start from the reconstructed image and apply different filters to improve the speckle pattern. Hence, it requires only a computer and access to the frame buffer of the ultrasound imaging system to perform its job. Moreover, with the advent of modern computing platforms and massively parallel processing hardware such graphics processing units (GPUs) that all became well within budget for ultrasound imaging systems, this approach seems like the logical starting point for practical purposes. From the technical point of view, post-processing methods can be categorized into linear, nonlinear, diffusion-based, and wavelet-based filtering methods [2]. The linear filters include such techniques as First-Order Statistics Filtering, Local Statistics Filtering with Higher Moments, and Homogeneous Mask Area Filtering [9][10][11]. The nonlinear filtering methods include Median Filtering, Linear Scaling Filter, Geometric Filtering, and Homomorphic Filtering [12][13][14][15]. The diffusion-based methods include several variants of Anisotropic Diffusion Filtering [16][17][18][19][20]. The wavelet-based methods mainly work using wavelet shrinkage using different wavelet families and levels of composition [21][22][23][24]. Hybrids between the above methods were also introduced [25][26][27].

Despite the relative success achieved by the present methods in reducing speckle in ultrasound images, there remains several problems that hinder the practicality of their use in clinical ultrasound. First, there is a gap between what the quality of the processed image means to researchers and clinicians. That is, the outcome of these methods may look smoother and hence better to the researchers but to the contrary such appearance may hide some features in the image that are important to the clinical sonographers. So, there is a need to develop better quality metrics that more accurately reflect the clinical view of the image quality [28]. Second, the focus only on reconstructed images may be the easiest way to address the speckle reduction problem but it certainly is not the optimal one. If a better solution to this problem is to be achieved, the different aspects of image formation must all be taken into consideration and optimized together to get the best results. This includes optimizing acquisition, beamforming, dynamic range compression, detection, sampling, quantization, scan conversion, and image reconstruction algorithms. Third, even though parallel processing has been around for a while now, very few reconstruction algorithms have been designed to work on parallel processing platforms. This is a clear disadvantage because they will not run in real-time and/or pose a scheduling problem in the processing chain in ultrasound imaging systems especially in complex, time-critical applications such as 4D imaging.

One of the important aspects of ultrasound image quality is how it is perceived by a human sonographer. In particular, the psychophysiological aspects of human vision have a profound effect on such things as contrast sensitivity and details resolution that influence diagnostic quality [28]. In [29], Campbell and Robson presented the concept of contrast sensitivity function (CSF) that define the effects of contrast and spatial frequency content on the visual detectability by a human observer. In Fig. 1, this effect is illustrated using a simulated grating with different spatial frequency and contrast simulated based on algorithms in [30]. As can be observed, the variations in the grating are not detectible above the CSF superimposed on the grating as a dashed line. This suggests that reducing the contrast for high spatial frequency image details can reduce their detectability by a human user. In the context of speckle reduction, the goal is to make their less detectible by the sonographer. Given that the speckle noise has high spatial frequency content, this suggests that reducing their contrast would reduce their visibility by a human sonographer.

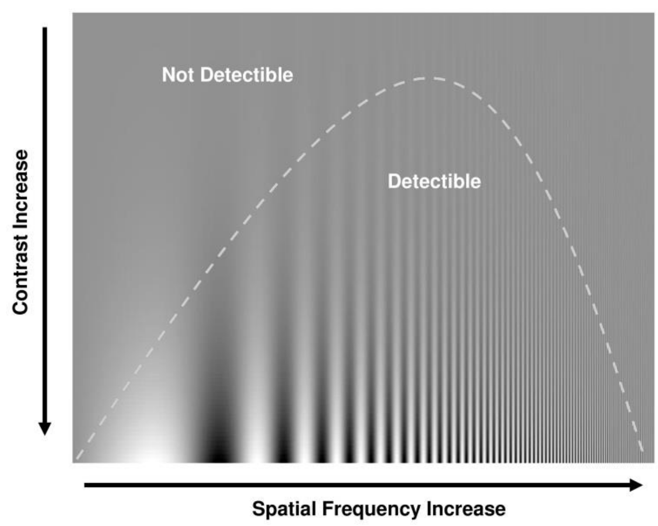

Fig. 1. The Campbell-Robson Contrast Sensitivity Function Chart where Visual Detection of Variation Depends on Both Contrast and Spatial Frequency as Outlined by the Separation with the Dashed Line.

In this work, a new method of speckle reduction in medical ultrasound imaging is developed whereby a user-controlled image display method adds a bias field map estimated from the original image that reduces speckle visibility. The new method relies on the contrast sensitivity function of the human visual perception to push the high spatial frequency content in speckle out of the visual detectability zone. This strategy does not affect the speckle pattern itself or change its statistical independence but rather allows the user to control how it is displayed to match subjective needs. The new method is experimentally verified using real ultrasound imaging data collected from a research system and compared to previous speckle reduction methods using quantitative image quality metrics.

III. METHODOLOGY

The speckle pattern in ultrasound images is characterized by a pseudo-random pattern with high contrast and high spatial frequency content due to its origin from the interference of many back-scattered waves. As a result, unlike random noise, it contains information about underlying tissue and may contribute diagnostic information in some cases. On the other hand, in many cases, the speckle pattern reduces the perceived ultrasound image quality and hence control over its visibility in the image is needed. In this work, it is proposed to take advantage of the characteristics of the contrast sensitivity function of the human visual system to develop a method that allows the visibility of speckle to be controlled by the user through appropriate contrast modification. This approach recognizes the importance of speckle as containing diagnostic information and addresses the subjective nature of image quality perception. According to this approach, reducing the contrast of speckle can improve image quality by reducing their visual detectability. The contrast is defined as the ratio of the maximum intensity to the average intensity. In order to verify this concept, a preliminary experiment was conducted where a speckle pattern from a real ultrasound imaging experiment was displayed along with the same pattern with different uniform intensity bias added to it. As this bias intensity increases, the contrast becomes lower according to its definition. In Fig. 2, the image to the left is the original speckle pattern while the other images show the same pattern with an increasing constant bias intensity added to the original as one moves to the right. As can be observed, the coarse visual appearance of the original speckle pattern gets finer as the bias intensity increases. Even though this confirms the validity of the concept, it is still not practical to just add a constant bias to the whole image because it may affect the contrast sensitivity of other areas of the image not containing speckle. A more suitable approach is to design a spatially-variant bias map that estimates a smooth local brightness level in different parts of the image. In this work, using a simple image denoising technique such as 2D median filtering with a large kernel as the bias field is proposed. This allows the differentiation of speckle from specular reflectors in the image. The weighted averaging of this bias map and the original image would result in a variable degree of speckle visibility depending on how the weight is selected and allows the user to select the level of speckle suppression subjectively. Given that, the weighted average may have dynamic range compared to the original, a simple adjustment of the dynamic range is done to maintain the appropriate display quality. A block diagram of the new method is shown in Fig. 3. The method accepts an original image in the form of a reconstructed image or as raw data collected by the imaging system. The original image is fed into two processing blocks. The first uses one of the present image-denoising filters for bias map estimation. In this work, a 2D median filter was used with a kernel size of nine to result in a fairly constant bias within the speckle pattern areas while varying with major interfaces to maintain contrast. It is conceptually possible to use other techniques to estimate that local bias field that serves as a local estimate of average intensity in the neighborhood. Then, the output from the image denoising filter and original image are used to obtain the final image using a weighted average. The weight used is selected by the user depending on the subjective desired outcome and application and applied to the original image. In order to ensure that the resultant image is displayed properly on the imaging system monitor, the dynamic range of the final image is adjusted to fit the dynamic range of the monitors (for example, 8-bit gray scale).

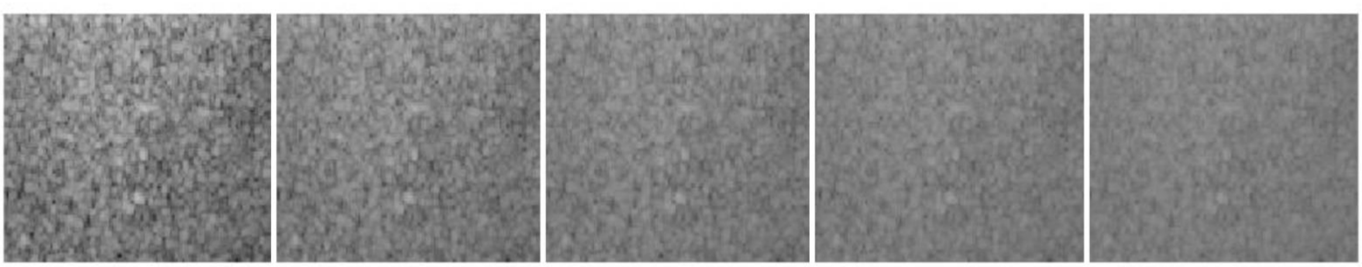

Fig. 2. Diagram Showing the Results of Adding a Constant Intensity Bias to the Original Image Shown to the Left. The Speckle Pattern Detectibility Decreases As Intensity Bias Increases From Left to Right Images.

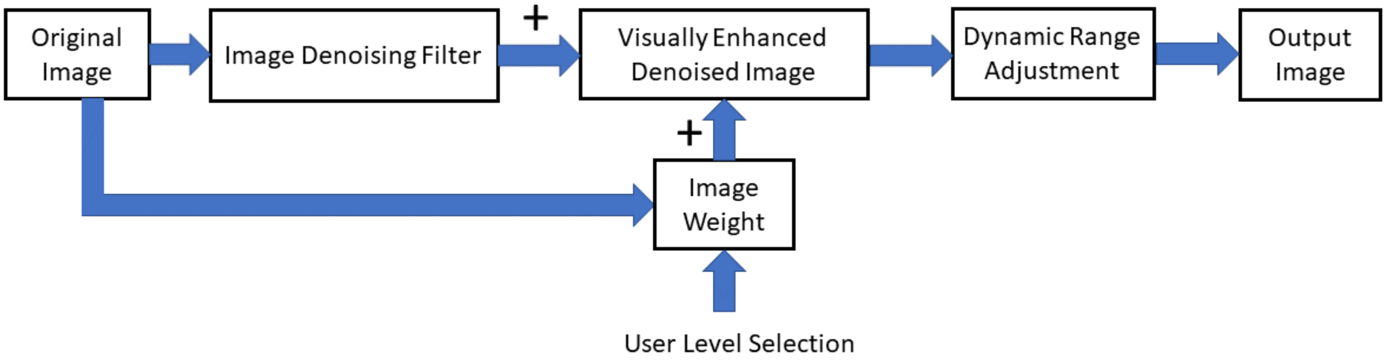

Fig. 3. Diagram Showing the Steps of the Porposed Technique Whereby Intensity Bias Map is Estimated using a Simple Image Denoising Filter and then used to Reduce Speckle Visibility in the Original Image.

IV. Experimental Verification

The ultrasound imaging data were collected using a Digison Digital Ultrasound Research system (Mashreq Company, Egypt). The system was equipped with a custom research interface to control image acquisition with ability to access and save raw radiofrequency sampled data for each collected image line. In order to make sure that the images are representative of different applications, the images were collected using several ultrasound array probes including convex array abdominal probe, small parts linear probe and a tight convex array endo-cavity probe. The imaging experiments were done for different clinical applications on human volunteers, as well as on a quality control tissue-mimicking phantom (Multi-Tissue Ultrasound Phantom CIRS Model 040GSE, CIRS Inc., U.S.A.). In each imaging experiment, a specific region was imaged using a specific imaging probe and a total of 10 images were collected for each application. The total number of imaging experiments done was 26 with a total number of images of 260. The research interface allowed the collection of raw image data at a sampling rate of 50 M Samples/s at 16 bits of quantization. Signal processing using filter-based Hilbert transformation for peak detection then resampling to obtain a total of 512 data samples per line (or stick). The number of image lines was 128 and this 512×128 array represents the stick data. The application of the new technique was done on the stick data using a bias field estimation from a 2D median filter with kernel size of nine and the weighting factor used to combine the bias field and original image was takes as 0.5. The dynamic range modification was done using simple window/level operation to ensure that the histogram of the combined image extends over the available display dynamic range of 8-bits. The image quality of output images is estimated using two quantitative image quality metrics of structural similarity index (SSIN) [31], and universal quality metric [32]. Given that each application may have different image characteristics, the image quality metrics from the 10 images collected for each of the 26 different imaging experiments were averaged to provide more reliable comparisons.

The final image reconstruction was subsequently performed using scan conversion and/or interpolation according to the array geometry and dimensions to display the image in the correct spatial format. All processing was done on Matlab 2022b (MathWorks, Inc.) using an educational license available through King Abdulaziz University. The computing platform consists of a personal computer with 11th generation Intel® Core™ i7-11700F running at 2.50 GHz clock and using a 64-bit Windows 11 Home Edition, with 32 GB of RAM.

V. Results and Discussion

The output image results from the new technique as compared to the original images and four representative techniques covering the current approaches in speckle reduction as applied to sample applications are shown in Fig. 4. The previous techniques considered are wavelet denoising [21][23], relaxed median (RMedian) denoising [14][15], speckle reducing anisotropic diffusion (SRAD) [17][16][18], and local statistics based filtering (Lee) [9][10]. In each of these techniques, the original technique is implemented with the implementation details suggested in the most recent variant. As can be observed, the new technique shows finer speckle pattern and less blurring as compared to present techniques. This is particularly evident in the linear array example at the bottom of the page where the texture is significantly smoother compared to other techniques without having a blurring problem as found with the techniques based on wavelet denoising and lee filter.

The performance of different techniques was quantitatively assessed using the structural similarity index and universal quality image quality metrics for each imaging experiment. The results are shown in Fig. 5. Each point on these plots represents the average of the respective image quality metric computed over the 10 images collected in each experiment. As can be observed, the proposed method had better metrics in the majority of experiments followed by SRAD and RMedian techniques.

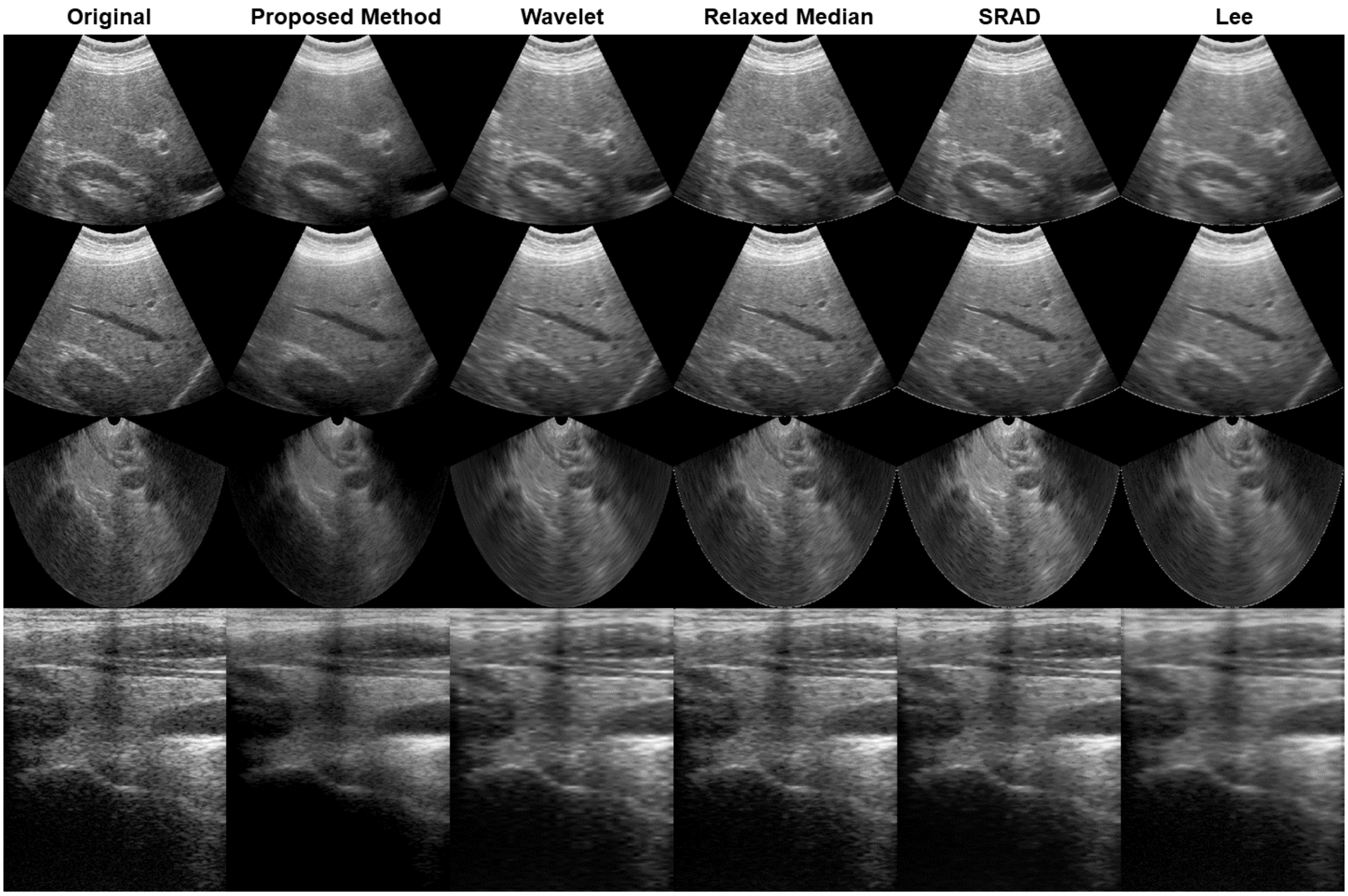

Fig. 4. Fig. 4. Diagram Showing the Output Image Results from the Porposed Technique as Compared to the Original Images and Four Previous Techniques. As Can Be Observed, the Proposed Method Offers Finer, Less Detectible Speckle Pattern Without Image Blurring.

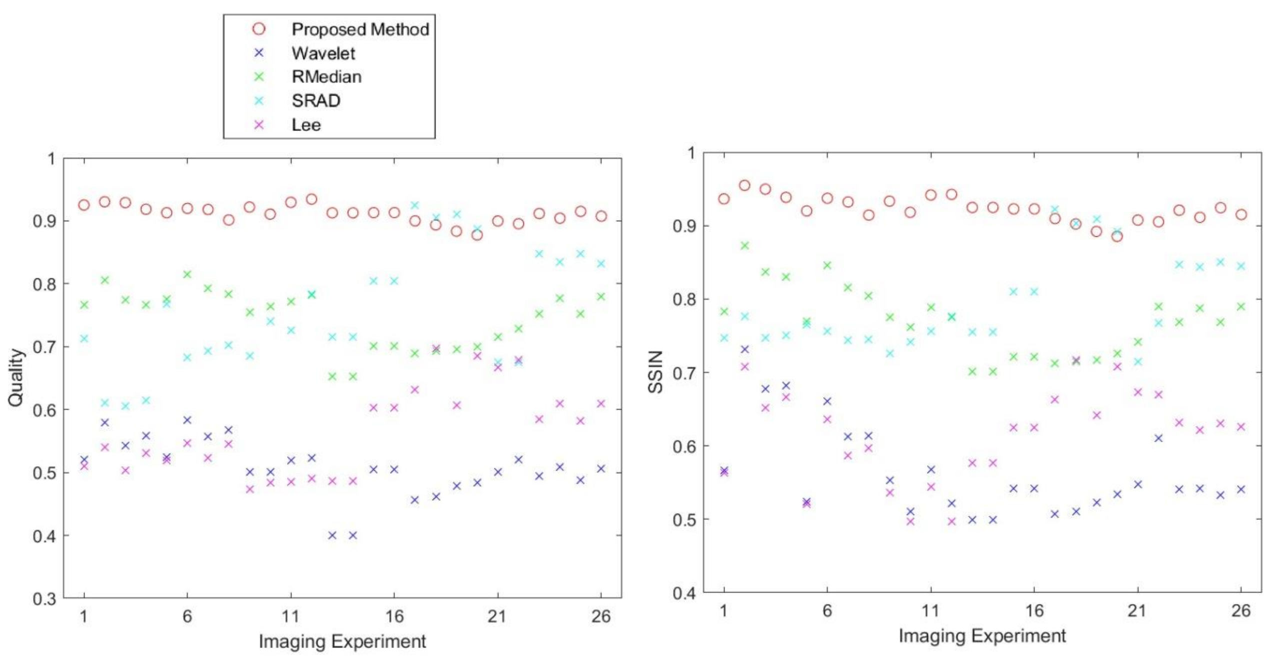

Fig. 5. The Performance Comparison of Different Techniques as Evaluated by Two Quantitative Image Quality Metrics for Each Imaging Experiment.

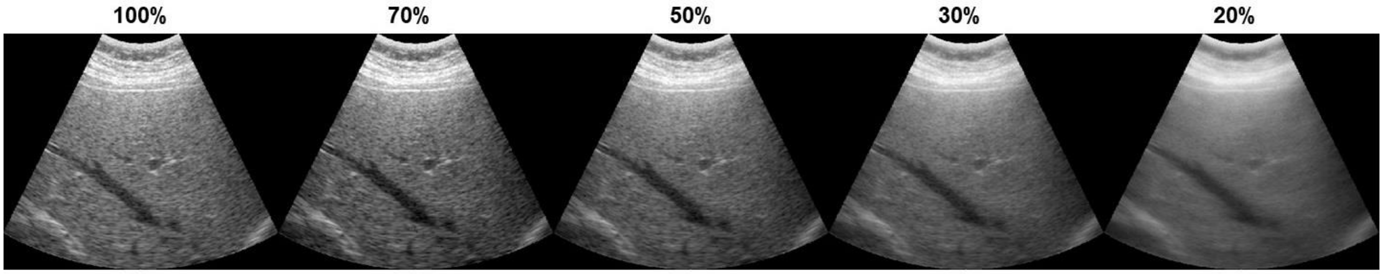

Fig. 6. Diagram Showing the Output Image for Different user Level Selections Starting from the Original Image (No Intensity Bias) on the Left With Higher Contribution of Bias Intensity From the Left to the Right Images.

To demonstrate the value of user level selection over the speckle visibility in the output image, the output image from the same experiment using levels of 100% (original image without adding intensity bias field), 70%, 50% (used in generating previous results), 30% and 20% are provided in Fig. 6. As can be seen, the level of speckle visibility decreases as one moves to a lower level of original image contribution to the weighted average. This comes at the expense of possible blurring depending on how the bias field is generated. Therefore, a selection of a level around 50% seems to strike a balance between the two requirements of reduced speckle and blurring. This allows the sonographer to adjust the level to what he peceives as the optimal image quality for improved diagnosis.

The challenge facing the broad adoption of the new methodology are mainly due to the way the implementation in real clinical settings. Usually, the sonographer looks at the real-time images on the monitor of the ultrasound imaging system to make the diagnosis while doing the scan. If the implementation is not done on the ultrasound imaging system itself, an external computer must be connected to the system to acquire the images, process them in real-time and then display them on a medical grade monitor. The computational complexity of the new method is essentially $\boldsymbol{O}(\mathrm{N}^2)$, which is of the same order as the image reconstruction process itself and does not pose any problems in real-time processing on modern computing platforms. The main problem in the external processing option lies in how the extensive measurements and calculations packages usually offered on ultrasound imaging systems can be accessed and used during the scan. Since asking the sonographer to use an external computer to control and display ultrasound images on an external monitor and use the built-in ultrasound imaging for measurements and calculations might be inconvenient to the doctor, the implementation as an integrated original equipment manufacturer module might be the best alternative.

VI. Conclusions

A new method of speckle reduction in medical ultrasound images based on adaptive shifting on the contrast sensitivity function of human vision is proposed. The new method offers an effective image enhancement strategy that reduces speckle while preserving diagnostically useful image features and allowing practical implementation in real-time for medical ultrasound imaging applications. The new method is used to improve the visual perception of image quality of ultrasound images by adding a local contrast bias to the areas with speckle noise. This allows the variations in image pixels due to speckle noise to be better perceived by the human observer as a result of the visual perception model. Furthermore, given that image quality perception is subjective, the level of added bias is controlled by a single parameter that accommodate the different needs for different users and applications. The new method is experimentally verified using real ultrasound imaging data from 26 imaging experiments with 10 images in each. The results are evaluated qualitatively by comparing appearance of images and quantitatively using two image quality metrics. The results demonstrate the performance of the proposed method and indicate its potential to offer better viewing conditions of ultrasound images, which translates to higher diagnostic accuracy.

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