ABSTRACT

This paper uses a new ultrasound tissue model to propose an ultrasound image deconvolution algorithm for improving the quality of ultrasound images. This model incorporates random fluctuations of the tissue signal within the received ultrasound RF echo signal, which has not been considered in the existing ultrasound imaging algorithms. To deal with the tissue image formation and noise reduction problems, a two-dimensional (2-D) blind deconvolution algorithm is presented in which a nonorthogonal wavelet transform is designed to adaptively estimate the tissue response. The performance of the algorithm is evaluated based on realistic simulation. The deconvolved images can show significant improvement in both the signal-to-noise ratio and the contrast ratio.

KEY WORDS
Ultrasound imaging, deconvolution, cepstrum, wavelet transform

1. Introduction

The non-invasive nature, low cost, portability, and real-time image formation make ultrasound imaging a valuable tool for medical diagnosis. However, ultrasonic images exhibit speckle artefacts which mask the presence of low cost lesions and hence reduce the ability of human observer to discriminate fine details in diagnostic examination. Speckle is caused by the constructive and destructive interference of backscattered signals due to unresolved tissue inhomogeneity.

Over the years, a number of image processing techniques such as weighted median filtering [1, 2], adaptive filtering [3, 4], wavelet shrinkages [5, 6, 7], and anisotropic diffusion [8, 9] are explored on the ultrasound envelope image to reduce speckles. Despite being simple and fast, these approaches were of limited success because of their inherent limitations in processing the image in the demodulated envelope signal domain.

The ultrasound images are severely blurred in both the axial and lateral directions. Factors originating from imaged tissues such as acoustic phase aberrations and velocity variations due to tissue inhomogeneity are important causes. The observed ultrasound image is, therefore, a distorted version of the actual tissue.

The compensation of these imaging distortions is a crucial issue for improving the quality of ultrasound images. Recognising that image formation process actually occurs in the RF (radio frequency) domain, signal processing techniques applied in the RF domain to obtain high quality image have been active [10]-[14]. Contemporary authors focused on the estimation of the spatially variant pulse-echo wavelet or PSF (point-spread function) of the imaging system. Abeyratne et al. [12] proposed to use higher order spectra based method in the estimation the 2-D PSF. Taxt [13, 14], however, suggested using the complex cepstrum method. These algorithms emphasized on obtaining an accurately estimated PSF and, indeed, overlooked the importance of noise suppression.

In this paper, we present a tissue signal model. The inclusive of the model in the received pulse-echo pressure field reveals that there are two different natures of noise sources existing in the received ultrasonic RF echo. One is inherent in the tissue response and the other is the measurement noise. A desirable ultrasound image can be obtained only when effects of both kinds of noise are suppressed.

To address this issue of suppressing the noise in the tissue response, we propose an algorithm with equal emphasis on PSF estimation and noise reduction. A key operation in the noise suppression is the application of wavelet decomposition to the estimated noisy tissue response for noise rejection. The design of the wavelet decomposition is based on the tissue response model which captures characteristics of the tissue signal and the field scattering noise.

The paper is organized as follows. Section 2 describes characteristics of the tissue and explains how the proposed new tissue signal model fixes into the convolution model of the RF echo. Section 3 presents the proposed 2-D blind deconvolution algorithm. In Section 4, computer simulations and performance of the algorithm are presented.
2. Problem Formulation

In medical ultrasound, a three-dimensional pulsed pressure field is emitted into the body and is scattered and reflected by small density and propagation velocity perturbations. The backscattered field is then received by the transducer for image formation. Therefore, tissue characteristics are often interpreted as a collection of point scatterers embedded in a uniform nonscattering medium. The biological variability associated with tissues, the spatial distribution, and the scattering strength associated with these scatterers are often described in statistical terms. Shankar [15] studied the statistics of the ultrasound echo by interpreting the ultrasonic backscattering from the tissue as point scatterers. The strength of scatterers was modeled as Gamma distribution [15, 16] and the locations of which were random and followed a uniform distribution [15, 16]. Thus, the structures within the tissue which are responsible for the backscattered ultrasonic field may be expressed as:

\[ s(\mathbf{r}_i) = \sum_{m=1}^{M} \alpha_m \delta(\mathbf{r}_i - \mathbf{r}_m) \]  

(1)

where \( s(\mathbf{r}_i) \) is called tissue response representing the underlying tissue structure, \( \mathbf{r}_i \) is a vector denoting the location of the scatterer, \( \alpha_m \) is the amplitude of the \( m^{th} \) scatterer of Gamma distribution which accounts for the variation in the scattering amplitudes within the tissue, and \( M \) is the number of scatterers in the range cell.

Insana et al. [18] represented the scattered field as a sum of the average field and the fluctuating field. The average field is called the coherent field and the fluctuating field is called the incoherent field which has the ensemble average of zero. The scattering region may also contain subresolvable periodic alignment of scatterers in addition to a collection of randomly located scatterers. In [17], Abeyratne et al. attempt to characterize the tissue based on a three-component point scatter model: a) the diffused component, b) resolvable periodic component, and c) a mixed non-Gaussian component. Georgia et al. [16], however, decomposes the RF echo into a coherent component and a diffused component. Thus, the model in (1) can also be represented as:

\[ s(\mathbf{r}_i) = f(\mathbf{r}_i) + n(\mathbf{r}_i) \]  

(2)

where \( f(\mathbf{r}_i) \) represents the mean scattering amplitude, the subresolvable or the resolvable periodic alignment of scatterers and \( n(\mathbf{r}_i) \) modeled the randomness in the variation of \( s(\mathbf{r}_i) \). Hence, \( s(\mathbf{r}_i) \) is considered the noisy tissue whereas \( f(\mathbf{r}_i) \) is the noiseless tissue response.

In the ultrasound image formation, the ultrasound images are blurred in both the axial and the lateral directions due to the finite resolution of the imaging system. Under the assumptions of linear propagation and weak scattering, an expression for the received pressure field was derived using the first-order Born approximation. The model for the received pulse-echo pressure field was presented as a convolution model in the following form [19]:

\[ y(\mathbf{r}_2, t) = v_{pe}(t) \ast s(\mathbf{r}_i) \ast h_{pe}(\mathbf{r}_1, \mathbf{r}_2, t) + w(\mathbf{r}_2, t) \]  

(3)

where \( \mathbf{r}_2 \) is the vector denoting the location of the transducer, ‘*’ and ‘\ast’ denote temporal and spatial convolution, respectively. \( v_{pe}(t) \) is the pulse-echo wavelet that accounts for the transducer excitation and the electromechanical impulse response during emission and reception of the pulse, and \( h_{pe}(\mathbf{r}_1, \mathbf{r}_2, t) \) is the modified pulse-echo spatial impulse response that relates the transducer geometry to the spatial extent of the scattered field.

Thus, \( f(\mathbf{r}_i) \) is the signal to be displayed. What we can measure is its smoothed version which has been corrupted by additive noise obscuring the finer details in the image. The smoothing process consists of a convolution in time with a fixed wavelet \( v_{pe}(t) \) and a spatial convolution with a spatially varying \( h_{pe}(\mathbf{r}_1, \mathbf{r}_2, t) \). They are known as the axial PSF and lateral PSF or, collectively, called the 2-D PSF in the following context. The noise term \( w(\mathbf{r}_2, t) \) explains the inevitable noise in the measured signal, accounting for electrical noise from amplifiers and for physical effects not explained by the convolution model.

3. Two-Dimensional Deconvolution

As in the above section, the ultrasound image formation process in the RF domain is interpreted as a spatio-temporal convolution between the tissue response and the ultrasonic system response, corrupted by additive noise. Alternatively, the convolution model (2) and (3) has the following expression in the sampled domain [10]-[14]:

\[ y(m, n) = v(m, n) * s(m, n) + w(m, n) \]  

(4)

and

\[ s(m, n) = f(m, n) + n(m, n) \]  

(5)

where \( y(m, n) \) is the ultrasound RF echo, \( v(m, n) \) is the 2-D PSF, \( s(m, n) \) is the noisy tissue response, both \( w(m, n) \) and \( n(m, n) \) are additive noise, and “*” denotes the discrete 2-D linear convolution operator with respect to the variables \( m \) and \( n \) representing the horizontal and vertical discrete sample coordinates. The process of recovering \( f(m, n) \) from \( y(m, n) \) is known as a blind deconvolution problem.

The proposed algorithm of this paper for solving the blind deconvolution problem consists of three steps. First, the
ultrasound system response is estimated from the measurements by applying a frequency-invariant linear filter in the complex cepstrum domain. Next, the estimated 2-D PSF is used in the inverse filtering to recover \( s(m,n) \).

The final step is the estimation of the noiseless tissue \( f(m,n) \) by decomposing \( s(m,n) \) with a nonorthogonal wavelet transform and utilizing a linear Bayesian estimator on the wavelet coefficients to give the estimated noiseless coefficients.

While the first two steps of the algorithm were known results in the literature [13, 14], the final step in dealing with tissue response model and tissue noise suppression is novel and has not been studied before. The details of the proposed algorithm are elaborated in the following.

### 3.1 Estimation of Two-Dimensional PSF using Complex Cepstrum

If the Fourier transform of the sequence \( y(m,n) \) exists, the complex cepstrum of \( y(m,n) \) is defined as [20]:

\[
\hat{y}(m,n) = F_2^{-1} \left[ \log_e \left( \hat{Y}(w_1,w_2) \right) \right]
\]

where \( F_2^{-1} \) denotes the 2-D inverse Fourier transform, and \( \hat{Y}(w_1,w_2) \) is the 2-D Fourier transform of \( y(m,n) \). The logarithm of the complex quantity \( Y(w_1,w_2) \) expressed in (6) is given by:

\[
\log_e \left( Y(w_1,w_2) \right) = \log_e \left[ Y(w_1,w_2) e^{\phi(w_1,w_2)} \right] = \log_e \left[ Y(w_1,w_2) + j \phi(w_1,w_2) \right]
\]

where \( \left[ Y(w_1,w_2) \right] \) and \( \phi(w_1,w_2) \) are the magnitude and unwrapped phase of \( Y(w_1,w_2) \), respectively.

For the complex cepstrum to exist, both the magnitude and phase must be continuous functions in the 2-D space. It is noted that the complex cepstrum is a periodic function in the phase. Hence, phase unwrapping algorithm and linear phase component removal procedure are required to ensure that the phase is continuous and periodic before the inverse 2-D Fourier transform in (6). The weighted least-squares (LS) phase unwrapping algorithm in [21] is used to obtain an unwrapped solution by iteratively minimizing the differences between the discrete partial derivatives of the wrapped phase data and the discrete partial derivatives of the unwrapped solution. Because the LS algorithm does not produce an unwrapped surface that is congruent to the wrapped phase, a postprocessing operation [22] is applied to approximately minimizes the number of discontinuities and thereby transforms the LS solution into a local optimal result.

For simplicity, we omit the noise \( w(m,n) \) in (4). If \( v(m,n) \) and \( s(m,n) \) have valid complex cepstra \( \hat{v}(m,n) \) and \( \hat{s}(m,n) \), the complex cepstrum has a property that the convolution in the time domain corresponds to the addition in the complex cepstrum domain. Thus we have [20]:

\[
\hat{y}(m,n) = \hat{v}(m,n) + \hat{s}(m,n)
\]

This additive property makes the estimation of \( \hat{v}(m,n) \) feasible by simple linear filtering. To separate signals which are combined by convolution with a frequency-invariant linear filter in the complex cepstrum is feasible in this case, since both signals occupy different band in the cepstrum domain [13, 14, 20]. To avoid the Gibbs ringing phenomenon, a 2-D Butterworth lowpass filter [13, 14, 23] is used. Since the phase information is retained, the complex cepstrum is invertible.

### 3.2 Estimation of Noiseless Tissue via Nonorthogonal Waveform Transform

A naive deconvolution would be to inverse the smoothing process \( v(m,n) \) directly to obtain \( s(m,n) \). However, such inverse filtering [23] can perform poorly in the presence of noise because the filter design ignores the noise process. Improvement of the restored quality is possible with the regularized Wiener inverse filter technique [23] which performs as an inverse filter at passband frequencies, and as a smooth roll-off filter at stopband frequencies of \( v(m,n) \).

Based on the proposed tissue signal model, the restored signal by the inverse filter is a noisy version of the tissue response. Therefore, we adopted a nonorthogonal wavelet transform [24, 25] which provides the flexibility to the wavelet such that it will always have a wave shape similar to that of the processed signal, so that the decomposition of the signal is highly efficient with fewer nonzero coefficients. This feature is particularly valuable when the underlying PSF is spatially variance as the wavelet is able adapted to the varying PSF to assure efficient decomposition throughout the received RF echo signal.

Let \( s \) denote the noisy tissue signal, \( h \) and \( g \) denote the discrete analysis filters, all arranged as one-dimensional (1-D) vectors, the discrete wavelet transform (DWT) has the following forward transform [25]:

\[
s^{(d)}_j = \left[ (D'g) \ast \right] \left[ \prod_{i=0}^{j-1} \left[ (D'h) \ast \right] \right] s
\]

\[
s^{(a)}_j = \left[ \prod_{i=0}^{j-1} \left[ (D'h) \ast \right] \right] s
\]

and the inverse DWT is given by:

\[
s = \sum_{j=0}^{J-1} \left[ \prod_{i=0}^{j-1} \left[ (D'h) \ast \right] \right] \left[ (D'g) \ast \right] s^{(d)}_j + \sum_{j=0}^{J-1} \left[ (D'h) \ast \right] s^{(a)}_j
\]

where \( J \) is the level of decomposition, \( s^{(d)}_j \) and \( s^{(a)}_j \) are the detailed and approximation wavelet coefficients, \( D^j \) is the
operator that inserts $2^j - 1$ zeros between the elements of a vector. $h(n)$ and $g(n)$ are the $n$th sample position of $h$ and $g$ respectively where $g(n) = \psi(-n)$ is sampled from a continuous wavelet $\psi(t)$ and has been normalized to have unit energy. $h(n)$ is an interpolation filter chosen such that $h_{2j}(-n) * h_{2j}(n)/\sqrt{2}$ where $h_{2j}(n)$ is the Daubechies-4 basis filter [24]. The synthesis filters are designed to be $\tilde{h}(n) = h(-n)/2$ and $\tilde{g}(n) = c_e g(-n)$ with $c_e > 0$. They are required to satisfy the relation $\tilde{h}(n) * h(n) + \tilde{g}(n) * g(n) = \delta(n)$ where $\delta(n)$ is the Kronecker delta.

The estimated axial PSF is resampled to twice of its frequency to cover the high frequency band. This treatment also expands its capability to cater for noise suppression of the ultrasound second harmonic signal. Therefore, two levels of DWT were adopted in our algorithm. The resampled wavelet was then fitted to Morlet wavelet $\psi_m(n) = e^{-\beta^2 n^2/2} e^{i 2 \pi f_0 n}$. Both the resampled PSF and the Morlet wavelet were tested under the admissibility condition of wavelet, and only the one that has a value closer to zero was used as the discrete highpass filter. Figure 1 shows the structure of the filterbank of the nonorthogonal DWT.

![Diagram](image)

Figure 1. Illustration of a single stage of (a) the nonorthogonal discrete wavelet transform, and (b) the inverse discrete wavelet transform.

The wavelet transform is a linear operation. Consequently, after applying the DWT on (5) we obtain a set of decomposed signals which are representations of the projections of $f(m,n)$ and $n(m,n)$ as 1-D vectors in the wavelet domain:

$$s^{(d)}_j = f^{(d)}_j + n^{(d)}_j$$

$$s^{(a)}_j = f^{(a)}_j + n^{(a)}_j$$

Assume that $f^{(d)}_j$ and $f^{(a)}_j$ are spatially uncorrelated, and the noise is of zero-mean, it can be shown that the global minimization of mean-square error (MSE) over the whole image within the constraint of a linear solution corresponds to a local minimization in a neighborhood of each sample. The local linear minimum MSE (LLMMSE) estimation [26] of the noiseless reflectance is:

$$\hat{f}_j(n) = \bar{f}_j(n) + \max \left[0, \frac{\sigma^2_{\hat{f}_j}(n) - \sigma^2_{\hat{f}_j}(n)}{\sigma^2_{\hat{f}_j}(n)} \right] \times \left[ y_j(n) - \bar{f}_j(n) \right]$$

(12)

where $\hat{f}_j(n)$ is the estimate of $f_j(n)$, and $\bar{f}_j(n)$ and $\sigma^2_j(n)$ are mean and variance of the wavelet coefficients estimated from a local window. For generalization, the superscripts ‘$\hat{\cdot}$’ and ‘$\bar{\cdot}$’ in (11) have been discarded in (12). The function $\max[\cdot]$ in (12) is introduced to ensure that the estimated signal variance, $\sigma^2_{\hat{f}_j}(n) - \sigma^2_{\hat{f}_j}(n)$, is not negative.

4. Computer Simulations and Discussions

Computer simulation was carried out to study the performance of the proposed algorithm under a severe scattering condition, where the scattering results in development of fully formed speckle.

4.1 Simulation of Ultrasound Image

To test our restoration algorithm on ultrasound images, we modeled an observed ultrasound image of 3cm by 3cm. The received RF backscattered signal was sampled at 18.6MHz and the step size of transducer along the lateral direction was set to 0.1mm. The model of the sampled ultrasound image is shown in (4) and (5). The ultrasound system impulse response $v(m,n)$ before the sampling and lateral translation operations is represented by $v(r,t)$ which has an aperture corresponding to lateral beam profile of 6mm and is separable [8], i.e., $v(r,t) = v(r)p(t)$, where $r$ is the scalar representation of the lateral coordinate and $t$ denotes the axial coordinate corresponding to (3) respectively. $v(r) = e^{-r^2/2\sigma^2}$ is the spatial response for the transmitting and receiving aperture with $\sigma_r = 0.95$ representing the beam-width of transmitting ultrasonic wave, and $p(t) = -te^{-4\pi^2\beta^2\sin^2(2\pi f_0 t)}$ is the transmitted pulse modeled as a sine modulated Gaussian function with the center frequency $f_0$ (3.5MHz) and the bandwidth $\beta$ (1.72MHz). The ultrasound system impulse response is normalized with respect to the total energy such that $\sum_{i,j} v^2(i,j) = 1$.

The function $s(m,n)$ being the noisy tissue response in (4) represents the underlying tissue structure and is simulated by random point scatterers. The backscattering scattering strength of the random scatterers has a Gamma distribution.
and they are randomly distributed in the tissue with a uniform distribution. The randomness in the variation of scatterers is expressed as the signal-to-noise ratio of the scattering amplitude which was set to 20 and the densities of randomly located scatterers were set to 5 scatterers/mm and they were uniformly distributed.

The simulated tissue was designated to give fully developed speckle and it has a cylindrical disc located at its central. The mean scattering strengths for the background and the cylindrical regions were assigned to be 25 and 99 respectively. Therefore, the received ultrasound echo signal, \( y(m, n) \), is a superposition of echoes from all the scatterers present in the scattering volume:

\[
y(m, n) = \sum_i \sum_j v(i, j)s(m-i, n-j)
\]  

(13)

To model the inevitable noise in the measured signal, \( y(m, n) \) is then corrupted by adding zero mean white Gaussian noise to give root-mean-square signal-to-noise ratio of 20 which is worst than that of the practical value.

4.2 Simulation Results

The sampled RF data of the receiving ultrasound echo signal in (13) has a size of 362 by 300. Each 2-D PSF estimate is based on sampled RF data from a rectangular block described by \((k, l, M, N)\) where \((k, l)\) is the upper left corner of the block which offsets from the \((m = 0, n = 0)\) coordinate. \(M\) and \(N\) are the horizontal width and vertical height of the rectangular block of data respectively.

The estimation of the 2-D PSF was performed in the complex cepstrum domain using a 2-D Butterworth lowpass filter. The parameters of the Butterworth filter were set to an order of 5 and a cutoff frequency of 0.5 from the origin for both the axial and lateral frequency axes. In the estimations, \(k\) and \(l\) were initially set to 20, and twenty PSFs were estimated from the blocks by varying \(k\) and then \(l\), with an increment at each time by 5. In order to examine the robustness of the estimated PSF in the algorithm, estimations were repeated under different settings of \(M\) and \(N\).

Figure 2 compares the axial and lateral PSF of the simulated PSF with that of the estimated PSF. As shown, the estimated axial PSFs were quite accurate in capturing the oscillating behavior of the pulsating wavelet. As for the estimation of the lateral profile, the algorithm is able to follow the simulated Gaussian-shaped hypothetical lateral PSFs except some slight peaks in the center of the responses. If there are oscillations in the actual lateral profile, we may obtain an improved estimation from the results obtained as in estimating the axial PSF. Therefore, the results show that the proposed algorithm is not affected by variations in the size of the data block.

The spatial extent of the ultrasound pulse-wavelet is short. This is the reason that the recorded ultrasound image can be tessellated into lattice and estimated the PSF in each of these lattices. If the dimension of the lattice is appropriately chosen such that it is approximately homogeneous, the averaged PSF can be incorporated into the regularized Wiener inverse filter to restore the signal. The average noise level will decrease with the number of PSF estimates.

Our proposed tissue signal model suggests that the restored signal is not yet the tissue response. Indeed, it is the noisy tissue response. To reduce the noise fluctuated in the tissue, we resort to the use of the nonorthogonal DWT for decomposition of the noisy tissue into wavelet coefficients. Since the designated wavelet is adapted to the estimated PSF, it was a high efficient decomposition whereby the noisy tissue signals were represented by few nonzero coefficients. In the wavelet domain, LMMSE estimator is used to estimate the noiseless tissue under a local window of 3 by 3. For fully developed speckle, the noisy tissue has...
a Gaussian distribution and LLMMSE estimator will produce optimal performance.

Two regions of interests (ROI) are identified on the simulated ultrasound image of 3cm by 3cm. These two ROIs define two homogeneous regions of 64 by 64 in the simulated tissue phantom. ROI 1 is located at the central of the cylindrical disc whereas ROI 2 is situated in the scattering background region. In order to assess the performance of the proposed algorithm, we studied the performance metric used by many authors. We observed that signal-to-noise ratio (SNR) and contrast ratio (CR) best described the visual evaluation by human observers. An improvement in the quality of the deconvolved ultrasound image should have a high SNR accompanied with a high CR. The SNR of both regions were measured to be -29.80dB and -37.64dB respectively, where the SNR is defined as the mean value of the specified region against its standard deviation.

The measured CR was -3.03dB, which is defined as the mean value of ROI 1 against that of ROI 2. Table 1 investigated the performance of the proposed algorithm by breaking it down into two stages. The term ‘INVERSE’ represents the ultrasound image after the inverse filtering whereas ‘INVERSE + NDWT’ indicates that the ultrasound image after the inverse filtering had proceeded to the LLMMSE estimation of the noiseless tissue coefficients by the nonorthogonal DWT. Results of the deconvolved ultrasound image in ‘INVERSE + NDWT’ can show a significant improvement in the SNR with slight improvement in the CR. This clearly indicates that the denoising in the wavelet domain worked inline with the proposed tissue signal model. The logarithmic compression of the original ultrasound envelope and the deconvolved image by the proposed algorithm are presented in Figure 3. The figures can show that the visibility of the embedded cylindrical object is improved and the size of the speckle is reduced in the deconvolved ultrasound image.

### Table 1. Performance of the proposed algorithm based on signal-to-noise ratio and contrast ratio. These values were tabulated in terms of decibel (dB).

<table>
<thead>
<tr>
<th>Data block (M, N)</th>
<th>INVERSE</th>
<th>INVERSE + NDWT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SNR1</td>
<td>SNR2</td>
</tr>
<tr>
<td>(64, 16)</td>
<td>2.6</td>
<td>2.6</td>
</tr>
<tr>
<td>(64, 32)</td>
<td>2.4</td>
<td>2.5</td>
</tr>
<tr>
<td>(64, 64)</td>
<td>2.5</td>
<td>2.6</td>
</tr>
<tr>
<td>(128, 16)</td>
<td>2.3</td>
<td>2.6</td>
</tr>
<tr>
<td>(128, 32)</td>
<td>2.6</td>
<td>2.3</td>
</tr>
<tr>
<td>(128, 64)</td>
<td>2.3</td>
<td>2.5</td>
</tr>
<tr>
<td>(256, 16)</td>
<td>2.4</td>
<td>2.5</td>
</tr>
<tr>
<td>(256, 32)</td>
<td>2.1</td>
<td>2.6</td>
</tr>
<tr>
<td>(256, 64)</td>
<td>2.1</td>
<td>2.3</td>
</tr>
</tbody>
</table>

### Figure 3. Ultrasound image. (a) Logarithmically compressed envelope of simulated image and (b) the deconvolved image.

## 4. Conclusion

In this paper, we used a new tissue model for ultrasound image formation. It is based on careful studies of the works presented by researchers working in the field of tissue characterisation. The incorporation of this model into the convolution expression of the ultrasonic RF echo explains the needs to further processing of the ultrasound image after inverse filtering, which has not been carried out in the existing results in the area of ultrasound image deconvolution. Our signal model points out the fact that even if there is no contribution by the external noise, there are still random fluctuations of the tissue signal within the received ultrasound RF echo frequency spectrum. In this paper, we addressed this issue and proposed an algorithm to alleviate both the noise in the tissue and that due to external...
inferences. The results showed that our proposed algorithm has achieved an improvement in both the SNR and the CR.

References:


