A Markov-Random Field Based Filter for Speckle Reduction in Ultrasound Imagery

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Abstract

The major performance limiting factor in visual lesion detection in ultrasound imaging is the speckle noise that makes the signal or lesion difficult to detect. Speckle is a form of multiplicative noise that corrupts medical ultrasound imaging making visual observation difficult.

This work presents an approach that utilizes the capability of MRFs in capturing spatially correlated signal-dependent patterns. The approach builds upon embedding the statistical and physical properties of speckle patterns into a MRF framework. With an effective MRF model at hand, a nonlinear, computationally efficient denoising filter is designed based on a conditional expectation of each pixel in the MRF.

The approach is tested in two simulations and on In-Vivo data. The first simulation is on a 3 by 3 image to visualize the estimation of each pixel based on the conditional expectation. The second simulation is performed on a 70 by 70 test image to quantify the methods ability to suppress speckle and maintain the edges, showing an improvement of 59% in SI, 146% in CSR and 441% in ENL.
Finaly In-Vivo data was filtered and compared with a median filtering and a Graph-cut based optimization method. Visual comparison between the original image and the filtered image, verifies the image quality increase due to the much lower speckle noise.

MRF-Speckle Model Description

The conditional probability density function (cpdf) of the intensity of the center pixel, i_k, given the four neighbors $i_{k_1}, i_{k_2}, i_{k_3}$ and i_{k_4} is given by

$$P_{I_k|I_{k_{1...4}}}(i_k|i_{k_{1...4}}) = exp\left\{-\sum_{j=1}^{4} ln\left[B(i_k,i_{k_j})\right] - \sum_{j=1}^{4}\frac{A(i_k,i_{k_j})}{B(i_k,i_{k_j})} + ln(\mathcal{I}_0[\frac{C(i_k,i_{k_j})}{B(i_k,i_{k_j})}]) - 3ln[p_{I_k}(i_k)]\right\} \quad (1)$$

where $A(i_k,i_{k_j}) = |\alpha_{r_{kk_j}}|^2 i_{k_j} + i_k$,$B(i_k,i_{k_j}) = \mathcal{O}_k \times (1 - |\alpha_{r_{kk_j}}|^2$ and $C(i_k,i_{k_j}) = 2\sqrt{i_k i_{k_j}}|\alpha_{r_{kk_j}}|$.
In the implementation phase of the proposed speckle reduction algorithm "$\mathcal{O}_k$" represents the true pixel intensity at index "k". $\mathcal{I}_0[]$ is a modified Bessel function of the firsst kind and zero-th order and $\alpha_{r_{k_i}k_j}$ is the coherence factor between the points k_i and k_j. Further the cpdf obtained in equation 1 has the form

$$P_{I_k|I_{k_{1...4}}}(i_k|i_{k_{1...4}}) = exp{-}U(i_k,i_{k_{1...4}}) \quad (2)$$

$$\text{where } U(i_k,i_{k_{1...4}}) = V_{C_1}(i_k) + V_{C_2}(i_k,i_{k_{1...4}}) \quad (3)$$

$$\text{and } V_{C_1}(i_k) = 3ln[p_{I_k}(i_k)],$$

$$V_{C_2}(i_k,i_{k_{1...4}}) = \sum_{j=1}^{4}\frac{A(i_k,i_{k_j})}{B(i_k,i_{k_j})} - ln[\mathcal{I}_0[\frac{C(i_k,i_{k_j})}{B(i_k,i_{k_j})}]] + ln\left[B(i_k,i_{k_j})\right]$$

The quantity $U(i_k,i_{k_{1...4}})$ is the energy function, or cost function, of the MRF; the terms $V_{C_1}(i_k)$ and $V_{C_2}(i_k,i_{k_{1...4}})$ are, respectively, the single-clique and the pair-clique potential functions. The cpdf in equation 2 and the energy function in equation 3 are both in terms of the coherence factor $\alpha_{r_{kk_j}}$. This coefficient represents the level of similarity that a pixel k has with one of its four k_k, $\{j = 1, \ldots, 4\}$.

Theory

Nonlinear Estimator of the True Image

Given a speckled image I, consider a nonlinear estimator of $\mathcal{O}_k$, the kth pixel of the true image $\mathcal{O}$, defined by the conditional expectation

$$\hat{\mathcal{O}_k} = E[I_k|I \setminus \{I_k\}] \quad (7)$$

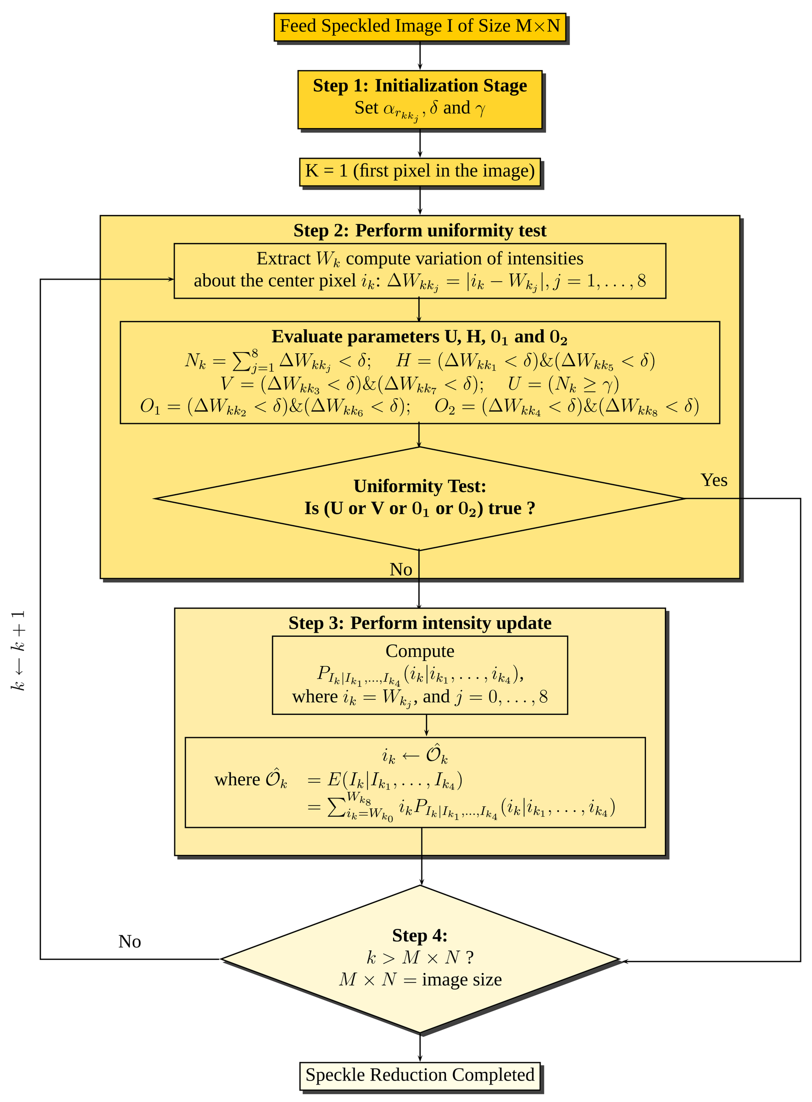
where $I_k \setminus \{I_k\}$ is the set of all pixels in the image excluding I_k. Now. using the Markovian nature of I, we can reduce the above estimator to

$$\hat{\mathcal{O}_k} = E[I_k|\mathcal{N}_k] \quad (8)$$

where $\mathcal{N}_k = \{I_{k_1}, I_{k_2}, I_{k_3}, I_{k_4}\}$ constitutes the set of intensities of the four adjacent pixels of k and the associated cpdf is given in eq. 1. The proposed estimate is explicitly given by

$$\hat{\mathcal{O}_k} = \int_0^\infty i_k exp[-U(i_k, i_{k_1}, \ldots, i_{k_4})]di_k \quad (9)$$

Restricting the set of possible values of i_k to the set of intensity values corresponding to pixels in the window does not alter the result significantly. Indeed, the probability of any pixel intensity outside the window W_k being nearly zero, their contribution to the estimated intensity value is negligible.



(a) Flowchart of the speckle-reduction approach

W_{k_2}	W_{k_3}	W_{k_4}
W_{k_1}	W_{k_0}	W_{k_5}
W_{k_8}	W_{k_7}	W_{k_6}

(b) window W_k centered on the kth pixel

ΔW_{k_2}	ΔW_{k_3}	ΔW_{k_4}
ΔW_{k_1}	0	ΔW_{k_5}
ΔW_{k_8}	ΔW_{k_7}	ΔW_{k_6}

(c) corresponding window after subtraction of i_k

Results

Image Quality Assessment Parameters

The effectiveness of the speckle reduction method was quantified using three different measures of speckle noise: 1) the speckle index, 2) the contrast-to-speckle ratio (CSR) and 3) the Effective-number-of-looks (ENL). The speckle index is related to the ratio of the local deviation in pixel brightness to the mean pixel brightness averaged over the entire image. The local deviation is defined as

$$\sigma(m,n) = \max_{-1 \leq a,b \leq 1}(f(m+a,n+b)) - \min_{-1 \leq a,b \leq 1}(f(m+a,n+b))$$

and the local mean is defined as

$$\mu(m,n) = \frac{1}{9}\sum_{a,b=-1}^{1}(f(m+a,n+b))$$

The speckle index, SI, is then defined as

$$SI = \frac{1}{MN}\sum_{m=1}^{M}\sum_{N=1}^{N}\frac{\sigma(m,n)}{\mu(m,n)} \quad (4)$$

The CSR is calculated by defining two regions of interest and using the mean pixel value and the pixel variance to quantify contrast $(\mu_1 - \mu_2)/\mu_1)$, and speckle noise $(\sigma_1^2 + \sigma_2^2)^{(1/2)}/\mu_1$. The ratio of these two quantities is termed CSR:

$$CSR = (\mu_1 - \mu_2)/(\sigma_1^2 + \sigma_2^2)^{(1/2)} \quad (5)$$

The ENL is computed by calculating the mean and the variance of the intensity over an area:

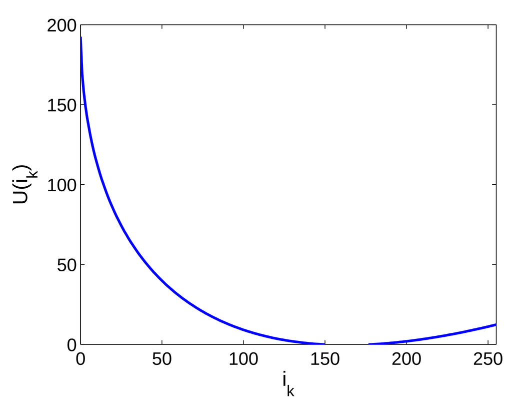
$$ENL = \frac{(K_0^{-1}\sum_{i \in A}\hat{I}_i)^2}{K_0^{-1}\sum_{i \in A}\hat{I}_i^2 - (K_0^{-1}\sum_{i \in A}\hat{I}_i)^2} \quad (6)$$

where A represents the set of indices corresponding to an area in the image $\hat{I}$ and K_0 is the number of elements in A.

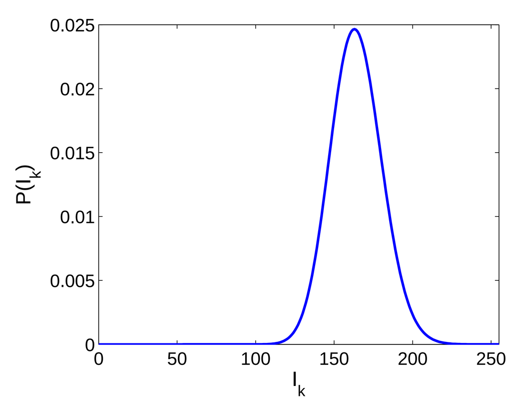
Simulation Results

182	182	163
163	i_k	145
145	163	182

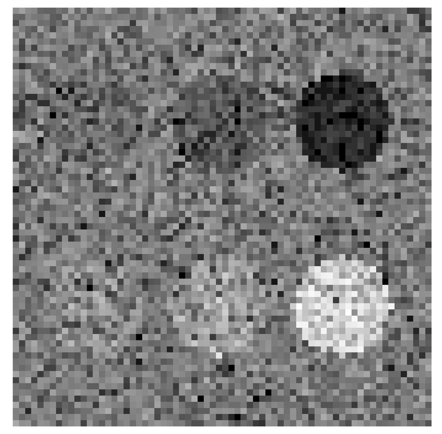
(a) Image of size 3×3. Numbers represent pixel intensities



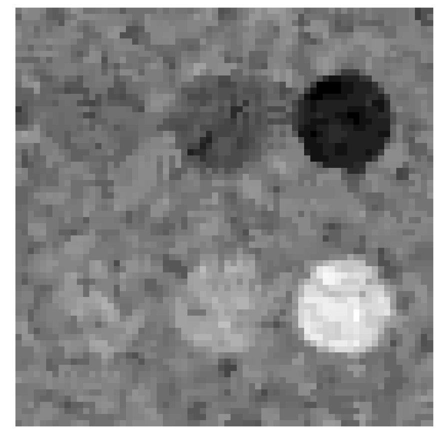
(b) Plot of the Gibbs energy function for the neighborhood values shown in (a)



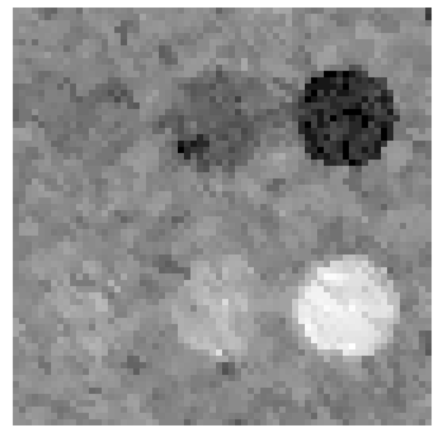
(c) Corresponding probability density



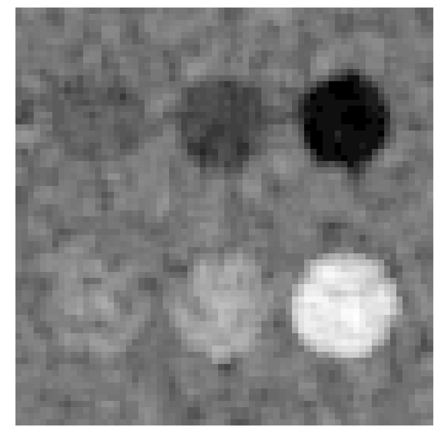
(a) Unfiltered Image



(b) Median filtered Image



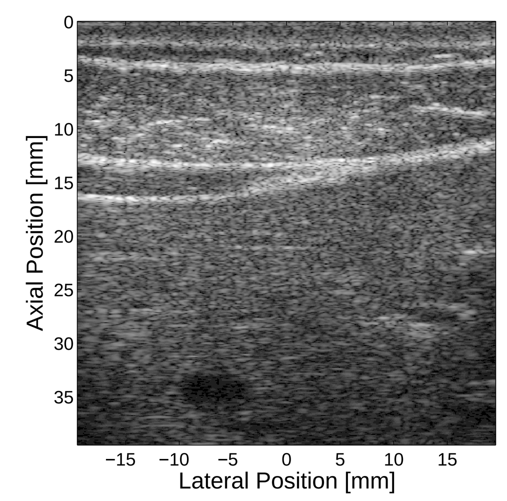
(c) MRF filtered Image



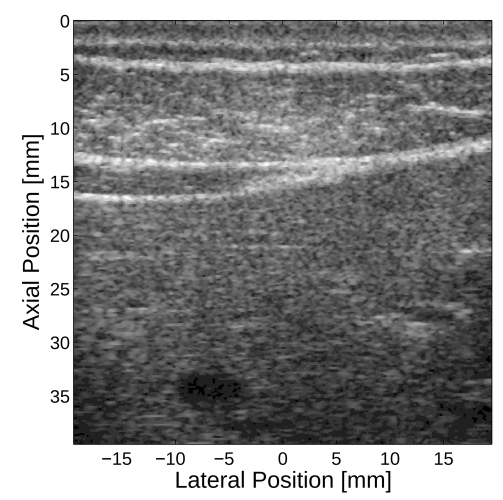
(d) Graph-cut based filtered Image

	Speckle Index	CSR	ENL
Unfiltered:	0.44	1.46	3.47
Median filter:	0.17	2.76	12.86
MRF method:	0.18	3.28	18.78
Graph-cut method:	0.13	4.00	26.38

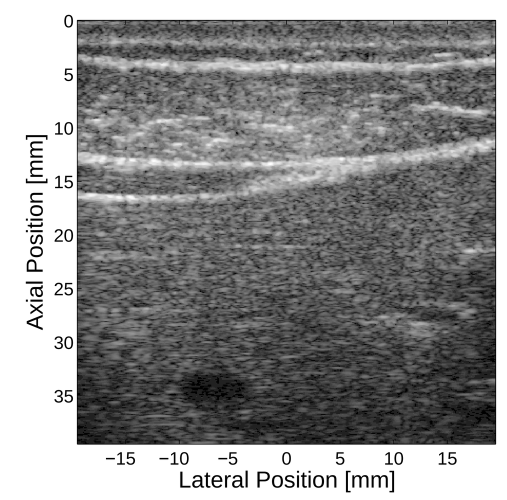
In-Vivo Results



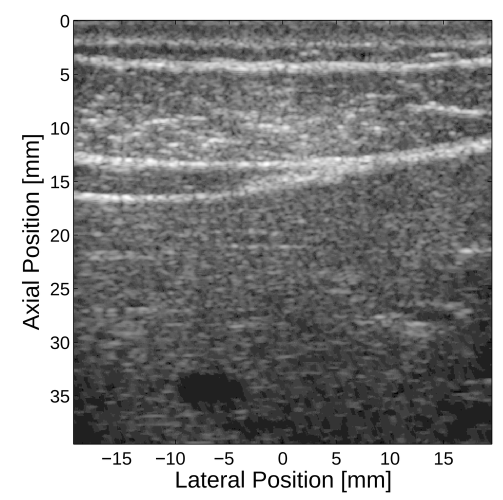
(a) Unfiltered image



(b) Filtered image



(c) Filtered image



(d) Filtered image

Ref (1): Ousseini Lankoande: A Markov-Random-Field Based Filter for Speckle Reduction in Ultrasound Imagery, Proc. Of SPIE, Vol 7265, Medical Imaging 2009
Ref (2): J.C.Dainty: Topic in Applied Physics: Laser Speckle and Related Phenomena. Springer-Verlag, N.Y., 1984