Compressive Re-Sampling for Speckle Reduction in Medical Ultrasound

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***Abstract*—A new method, Compressive Re-Sampling (CRS), is introduced to reduce the effect of speckle noise, a granular noise inherent in all coherent imaging technologies. The new method is motivated by the successful applications of compressive sensing (CS) to image processing and wireless communications. While compressive sampling is focused on acquiring signals at reduced data rates or reduced acquisition time, the goal here is to provide a speckle noise reduction method while preserving the original resolution and enhancing the contrast for diagnostic medical imaging applications. Initial results show an average SNR improvement of 12 dB.**

Keywords-compressive sensing; speckle noise; ultrasound; re-sampling; compressive re-sampling

I. INTRODUCTION

The use of the L1 norm to implement sparseness constraints for signal recovery has been known for some time [1]. The sparseness constraint was shown to be sufficient to recover a Nth dimensional signal consisting of only K nonzero elements with only partial information regarding the measurements [1]. The seminal papers by Donoho [2] and Candes [3] showed that the Nth dimensional signal can be recovered from significantly less than N measurements, on the order of log(N)*K measurements under the mild conditions of restricted isometry property (RIP). This observation created a great interest in compressive sampling techniques to lower the number of measurements needed to reconstruct a signal.

In this paper we introduce a new method we call Compressive Re-Sampling (CRS) [4-6]. The CRS method is used to reduce noise such as speckle noise by randomly selecting J subsets of the signal samples with replacement to reconstruct J signal estimates which are then averaged to reduce the noise of the final estimate. The idea of resampling in CRS is similar to resampling in machine learning where a number weak classifiers are combined to form a strong classifier. In CRS a number M of noisy estimates are combined to form a noise reduced estimate. In this paper the simple DFT matrix is used to form the J noisy estimates of the sparse N dimensional signal and averaged to form a noise reduced estimate. The CRS method is shown to significantly increase the SNR of simulated and measured clinical ultrasound signals over reconstruction with complete information, i.e., the full N measured samples.

The idea of re-sampling in CRS is similar to re-sampling in machine learning where a number of weak classifiers are combined to form a strong classifier. In CRS, a number J of noisy estimates are combined to form a noise reduced estimate.

Medical ultrasonography is a valuable imaging technology for visualizing subcutaneous body structures for medical diagnostics. The ability to provide live imagery also makes this technology suitable for guiding interventional procedures such as biopsies and aspirations. Ultrasound imaging is non-ionizing, non-invasive and more cost effective than many other medical imaging modalities.

However, ultrasound imaging suffers from speckle noise, an inherent characteristic of all coherent imaging techniques due to the presence of sub-resolution scatterers. Speckle noise produces a reduction in contrast resolution which is responsible for the overall lower effective resolution of ultrasound compared to x-ray or MRI imaging. In the case of breast imaging, ultrasound speckle can mask small details such as low contrast tumors or microcalcifications, which may be an early indication of breast cancer. This limitation prevents ultrasound from displacing mammography as the gold standard for breast cancer screening. In conventional pulsed ultrasound imaging systems, de-noising techniques are used to minimize the effect of speckle noise. However, research shows that there is a tradeoff between the effectiveness of speckle reduction techniques and image resolution.

The purpose of this study is to examine speckle reduction methods using the basic framework of compressive sampling in order to maintain the image resolution while reducing the effects of speckle noise in order to improve lesion detectability in the presence of speckle noise. This is particularly important for detecting microcalcifications in breast images which are typically obscured by speckle noise and are indicative of an early form of breast cancer known as ductal carcinoma in situ (DCIS).

Recent research studies have explored the use of compressive sensing (CS) on ultrasound imaging [7-9]. In particular the principles of CS can be used to reduce the number of samples or data rates needed during acquisition

which is important for real-time high resolution imaging modalities such as ultrasound. CS applied to the ultrasound RF signal exploits the signal's narrowband properties in the frequency domain and uses the Fourier Transform as the sparsifying basis.

II. Prior Work

Speckle reduction in ultrasound imaging as well as other coherent imaging technologies has been an active area of research for many years. Fully formed speckle (FFS) is characterized as multiplicative noise and is modeled as a Rayleigh random variable with a constant SNR of 1.92 dB. Speckle reduction methods for ultrasound imaging include compounding (averaging) methods and post-processing (filtering) techniques.

A. Compounding Methods for Speckle Reduction

Compounding techniques [10, 11] are based on acquiring several images of the same target and averaging the images to form a composite image with reduced speckle. Spatial compounding is based on averaging images from different scan directions while frequency compounding is based on averaging images acquired at different frequencies. These techniques may improve the SNR of the composite image and reduce the overall energy of the speckle noise but come at the expense of lower overall image resolution due to the averaging process. Compounding methods also come at the expense of additional hardware complexity and expense.

B. Post-Processing Methods for Speckle Reduction

Post-processing methods for speckle noise reduction are based on applying signal processing software algorithms to the acquired ultrasound image data. Filtering techniques that have been examined for speckle reduction include mean filters, median filters, Kaun and Lee filters, Frost filters and diffusion filters [12-16]. The goal of filtering techniques is to remove the speckle noise, improve overall SNR while preserving the fine details in the image that are critical for accurate detection and classification of lesions. Kaun and Lee filters, the Frost filter and other techniques are based on finding heuristic rules to optimize the balance between low pass filtering or averaging in the homogeneous areas of the image and all pass filtering or preserving the signal in the areas that are determined to contain edges and point features in the breast tissue. Diffusion and median filtering are non-linear filtering techniques designed to preserve and enhance edge information while smoothing out or suppressing the granularity of speckle noise, providing an overall perceptually better quality image.

Multi-scale approaches [16] have also been explored for reducing speckle noise in pulse-echo ultrasound systems. Wavelet-transform based multi-scale approaches are based on thresholding methods to reduce the noise components in the original image [16].

However, all filtering methods, whether single-scale or multi-scale, have an inherent tradeoff between smoothing out or suppressing speckle noise and preserving high frequency details that are critical for accurate detection and diagnosis of suspicious areas.

III. Compressive Re-Sampling (CRS) for Speckle Noise Reduction

The algorithm presented here for speckle noise reduction overcomes the limitation of loss in resolution while decreasing speckle noise by using an average of reconstructed noncoherent images, each of which is formed using a random subset of frequencies that are sampled over an entire bandwidth of an image [4-6]. The use of the full bandwidth maintains the resolution in the time/space domain. The random thinning of the Fourier components for each estimate provides estimates that are uncorrelated in terms of speckle, and can be averaged to lower the speckle seen in the compound image. This approach can be compared to frequency or spatial compounding methods used in the front-end of many high-end ultrasound devices which produce multiple views that are averaged to reduce the effects of speckle noise. The original frequency compounding technique produces estimates of the signal based on small non-overlapping frequency bands and these much smaller bandwidths significantly impact the resolution of the resulting image, resulting in a loss of fine details and tissue structure that is useful for accurate diagnosis.

Unlike CS techniques applied to the ultrasound RF signal for data acquisition, here we look at the dual problem. The reconstructed ultrasound image (B-Scan or A-Scan) assumes the sparseness constraint and the Inverse Discrete Fourier Transform (IDFT) forms the sparsifying basis. The technique introduced here takes advantage of the sparseness of the ultrasound image in the time domain in order to produce estimates of the signal based on subsampling the frequency components with substitution over the entire original bandwidth. J estimates of the signal based on keeping M random frequency components are combined noncoherently in the time (space) domain in order to produce an estimate of the image that greatly reduces the effect of speckle noise while preserving the original tissue details and structure. Because the technique does not depend on separating the signal into nonoverlapping small frequency bands, J can be much larger than typical frequency or spatial compounding techniques reducing the noise more effectively due to the large number of estimates that are combined for the final image.

Let x(t) be the time domain ultrasound signal and the discrete Fourier Transform of x(t) is denoted as X(w). Random binary masks of length N are produced where the number of 1's in any sequence is equal to M and the number of 0's is equal to N-M where M << N. These binary masks are expressed as B^j where

$$\begin{aligned} B^1 &= [1, 0, 1\ldots B(\mathrm{N})^1] \\ B^2 &= [0, 0, 0\ldots B(\mathrm{N})^2] \\ &\ldots \\ B^{\mathrm{J}} &= [1, 1, 0\ldots B(\mathrm{N})^{\mathrm{J}}] \end{aligned} \tag{2}$$

Estimates of the signal are generated by multiplying the J masks with the complex Fourier components and keeping J sets of M components chosen randomly, that is

$$X(\mathrm{w})^{\mathrm{j}} = X(\mathrm{w}) * B^{\mathrm{j}} \tag{3}$$

producing J estimates of the signal,

$$X(w)^1 = [X(1), 0, X(3) \ldots X(N)*B(N)^1]$$
$$X(w)^2 = [0, 0, 0, \ldots X(N)*B(N)^2]$$
$$\ldots \qquad (4)$$
$$X(w)^J = [X(1), X(2), 0, \ldots X(N)*B(N)^J]$$

The inverse DFT or FFT of the J re-sampled estimates is calculated and the analytic signal is used to noncoherently combine the estimates in the time (or spatial) domain, i.e.:

$$x(t)^j = x(t)^j + j\,(x'(t)^j) \qquad (5)$$

where x'(t) denotes the Hilbert transform of x(t). The J estimates are combined by taking the average of the magnitude at each time t or pixel location. The magnitude is given by

$$x_{mag}(t)^j = ((x(t)^j)^2 + (x'(t)^j)^2)^{1/2} \qquad (6)$$

and the final estimate of the noise reduced signal is expressed as

$$x_{mag}(t) = 1/J \sum_j x_{mag}(t)^j. \qquad (7)$$

IV. Results on Clinical Data

The CRS algorithms were applied to simulated A-Scans with varying amounts of speckle noise and the improvement in SNR is shown in Fig. 1. On average, the SNR improvement on simulated data with varying degrees of speckle noise is 12 dB. Fig. 2 and 3 correspond to A-Scans of breast tissue that were collected on a Siemens Acuson S2000 device by trained radiologists. The CRS method significantly reduces the variance of the speckle noise while preserving small details and structures that appear as peaks in the post processed signal. B-Scan improvements on clinical data are illustrated in Fig. 4-6. We apply the CRS method described here as well as the CRS framework to estimate magnitude and phase statistics [5-6] which are combined to produce the results shown in Fig. 4-6. The B-scans were collected by highly trained radiologists using the Siemens Acuson S2000 high-end cart-based ultrasound system. All parameters were optimized by radiologists for viewing and diagnosis including a spatial compounding feature and a speckle reduction feature. The images are of breast lesions assessed by radiologists as BI-RADS® 4 (suspicious abnormality) or BI-RADS® 5 (highly suggestive of malignancy) after a screening mammogram and diagnostic ultrasound and recommended for biopsy. Fig. 4 corresponds to a lesion where the radiologist recorded microcalcification findings on the mammogram but not on the original ultrasound. The biopsy for this lesion was found to be positive for malignancy. The image processed with the CRS method shows clearer lesion boundaries (dark area upper left quadrant), clearer tissue structure and small white specks that appear to be microcalcifications. Fig. 5 shows a highly irregularly shaped mass in the lower left quadrant and the CRS method provides an image where the tissue structure and lesion details are enhanced to assist in a more accurate diagnosis. Fig. 6 shows a lesion in the upper central portion of the image and the CRS method enhances the lesion characteristics, tissue structure and small details such as microcalcifications. A larger clinical trial is planned in order to collect clinical data to support improved diagnostic accuracy and visibility of microcalcifications.

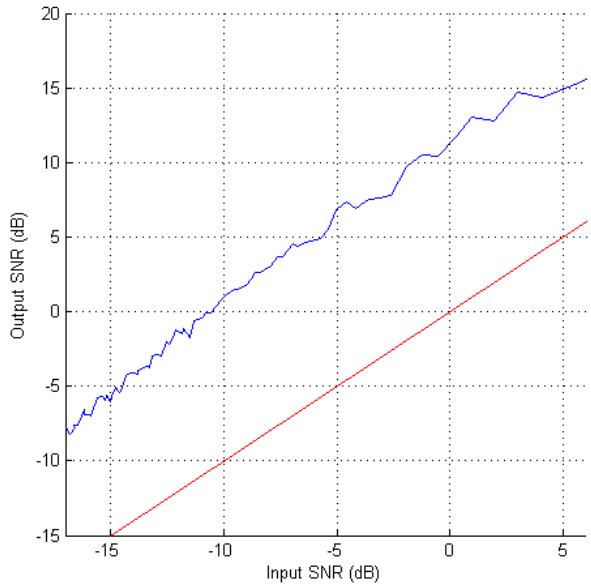

Figure 1. SNR Improvement Plot. The average SNR improvement on simulated data is 12 dB.

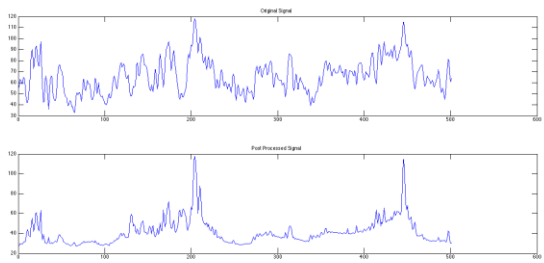

Figure 2. Clinical Breast Ultrasound A-Scan (top) and speckle reduced A-Scan (bottom) using the CRS Method

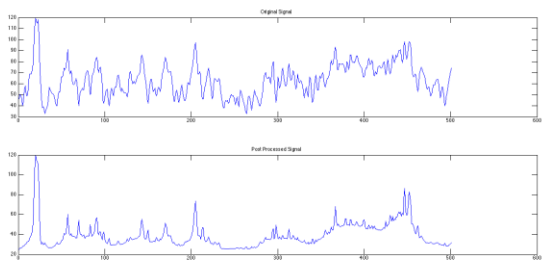

Figure 3. Clinical Breast Ultrasound A-Scan (top) and speckle reduced A-Scan (bottom) using the CRS Method

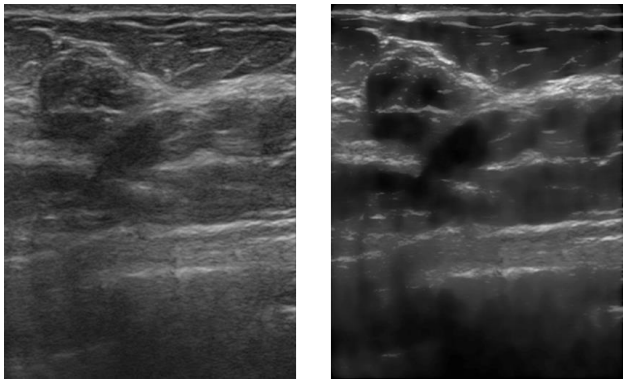

Figure 4. Original B-Scan optimized by radiologist (left) and Processed B-Scan using the CRS Method (right)

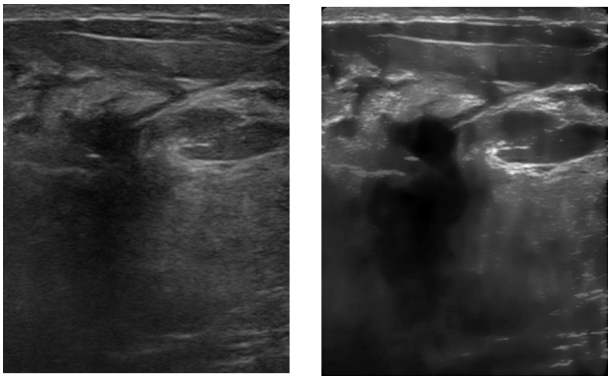

Figure 5. Original B-Scan optimized by radiologist (left) and Processed B-Scan using the CRS Method (right)

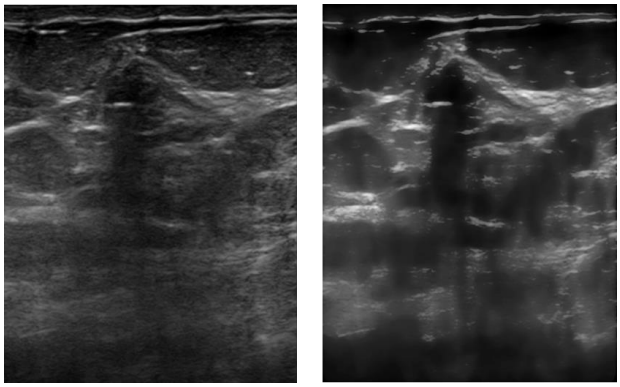

Figure 6. Original B-Scan optimized by radiologist (left) and Processed B-Scan using the CRS Method (right)

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