Compressive Re-Sampling for Speckle Reduction in Medical Ultrasound

Professor Richard Mammone
Rutgers University

Email Phone Number

Christine Podilchuk, Lev Barinov, Ajit Jairaj and William Hulbert
ClearView Diagnostics Inc.

Outline

- Problem: Speckle Noise in Ultrasound Imaging
- Previous Methods for Speckle Noise Reduction
- Technical Approach: Compressive Re-Sampling
- Preliminary Results
  - Simulated Data
  - Clinical Data
  - Recognition Performance
- Questions

The Problem: Breast Cancer Detection & Diagnosis

Mammography

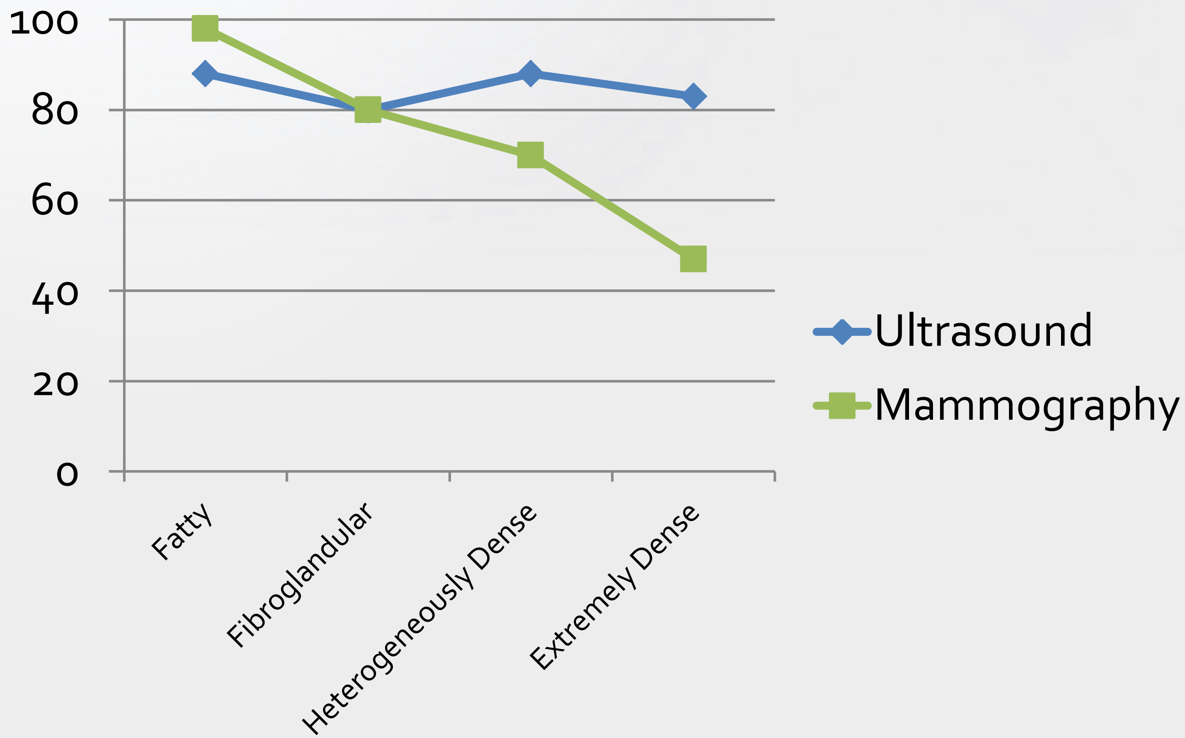
- Remains the “gold standard” for breast cancer screening
- Visualizes microcalcifications due to malignancies including early-stage ductal carcinoma in situ (DCIS)
- Fewer false positives than Ultrasound
- Not effective at imaging women with dense breast tissue
- Ionizing

Ultrasound

- FDA approved for diagnosis, not screening
- Speckle noise, inherent in all coherent imaging systems, results in lower contrast and effectively lower resolution, poorer quality image
- More false positives than mammograms
- Effective in imaging dense breast tissue which is 4-6 times more likely to develop cancer than non-dense tissue
- Non-ionizing

The Problem: Dense Breast Tissue

Imaging Sensitivity as a Function of BI-RADS Breast Density



Increasing BI-RADS density classification results in mammogram sensitivity dropping from 100% to 47% while ultrasound remains in the 80-88% for all breast densities (Source: Berg, 2004)

The Problem: Speckle Noise in Ultrasound

- Screening Breast Ultrasound Trial (ACRIN 6666) (JAMA 2008) showed an increase in sensitivity from 78% with mammograms alone to 91% with mammograms + ultrasound for women with dense breasts
- Screening US may depict small, node-negative breast cancers not seen on mammography
- Ultrasound has not been able to replace mammography for screening due to speckle noise which masks small, low-contrast lesions and microcalcifications, a potential early indicator of breast cancer

Imaging Modality	Diagnostic Accuracy	Pos. Predictive Value of Biopsy
MAMMO	.78	22.6
US		8.9
MAMMO + US	.91	11.2

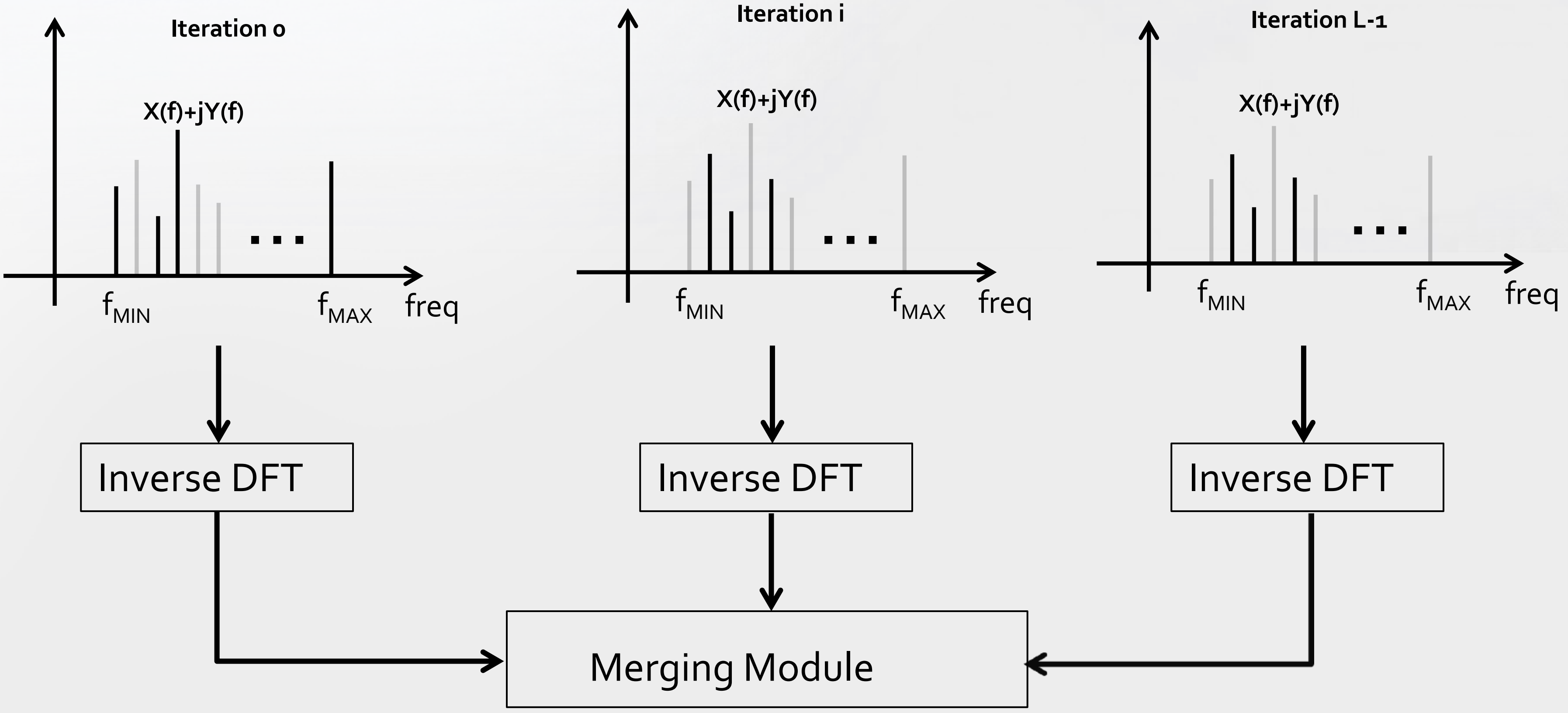
Previous Methods for Speckle Reduction

- Fully formed speckle (FFS) is multiplicative noise modeled as a Raleigh random variable with a constant SNR = μ / σ = 1.91 dB
- Speckle reduction techniques for ultrasound imaging include compounding techniques and postprocessing (filtering) techniques.
- Frequency and spatial compounding:
  - Additional hardware/acquisition time required.
  - Frequency compounding averages images acquired in different frequency bands
    - results in a loss in resolution due to the smaller bandwidth in each image.
  - Spatial compounding averages images acquired in different scan directions
    - results in a loss in resolution/accuracy due to spatial shifts between views.
  - Reduces the noise by a factor of $(L)^{1/2}$ where L is the number of estimates acquired.
- Filtering techniques such as Kaun and Lee, Diffusion, Median, Wavelet (denoising by soft thresholding), Laplacian pyramid are based on smoothing out the areas due to speckle noise while attempting to preserve edges and other details. Smoothing can result in a loss of small, high frequency details such as microcalcifications, a sign of ductal carcinoma in situ (DCIS), an early stage of breast cancer.

Technical Approach

- Novel speckle reduction technique is inspired by fundamentals of compressive sampling/sensing.
- Compressive sampling is motivated by reduced acquisition time or data rate.
- Compressive Re-sampling takes advantage of the ability to recover an estimate of the signal with fewer samples in order to provide multiple estimates that can be used to reduce speckle noise and enhance tissue and lesion detail.
- Compressive Re-sampling randomly samples the frequency components *over the entire bandwidth* in order to provide an estimate that does not reduce the overall resolution of the final image.
- The number of estimates L that can be acquired using this technique is very large so that the reduction in noise by $(L)^{1/2}$ is significant

Technical Approach



Technical Approach

x(t): K-sparse ultrasound signal
X(f): DFT{x(t)}
B: Random binary mask of length N with M "1"s and (N-M) "0"s where M<<N
L: Number of re-sampled estimates

$$B^1 = [1, 0, 1 \ldots B(\mathrm{N})^1] \qquad X(\mathrm{f})^1 = [X(1), 0, X(3) \ldots X(\mathrm{N})*B(\mathrm{N})^1]$$

$$B^2 = [0, 0, 0 \ldots B(\mathrm{N})^2] \longrightarrow X(\mathrm{f})^2 = [0, 0, 0, \ldots X(\mathrm{N})*B(\mathrm{N})^2]$$

$$\ldots \qquad \ldots$$

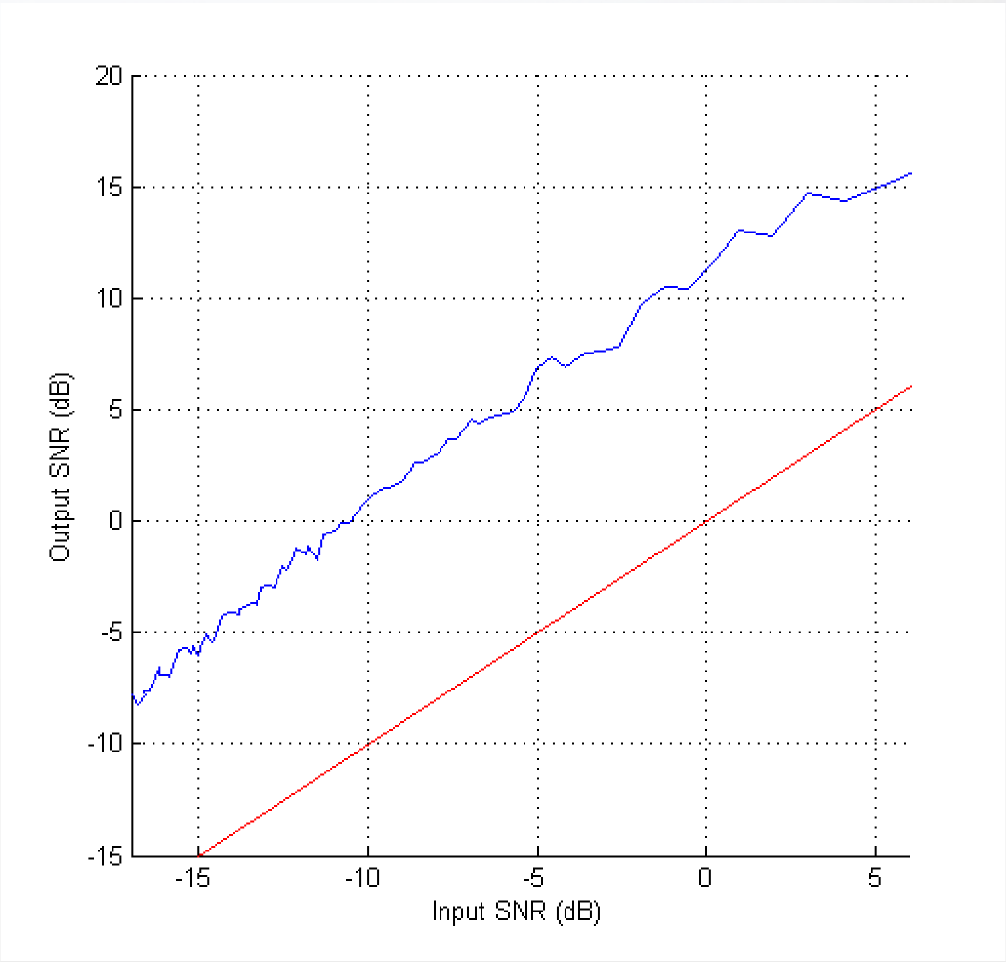
$$B^L = [1, 1, 0 \ldots B(\mathrm{N})^L] \qquad X(\mathrm{f})^L = [X(1), X(2), 0, \ldots X(\mathrm{N})*B(\mathrm{N})^L]$$

$$x(\mathrm{t})^i = x(\mathrm{t})^i + j\,(x'(\mathrm{t})^i)$$

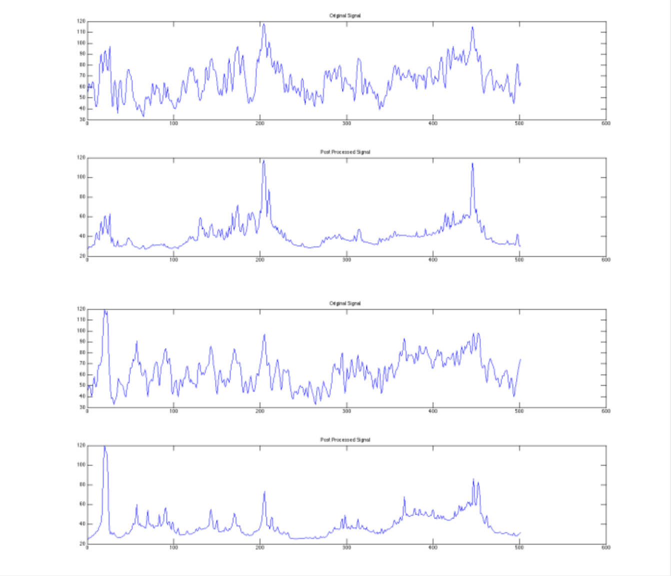
$$x_{mag}(\mathrm{t})^i = ((x(\mathrm{t})^i)^2 + (x'(\mathrm{t})^i)^2)^{1/2}$$

$$x_{mag}(\mathrm{t}) = 1/L \sum_i x_{mag}(\mathrm{t})^i$$

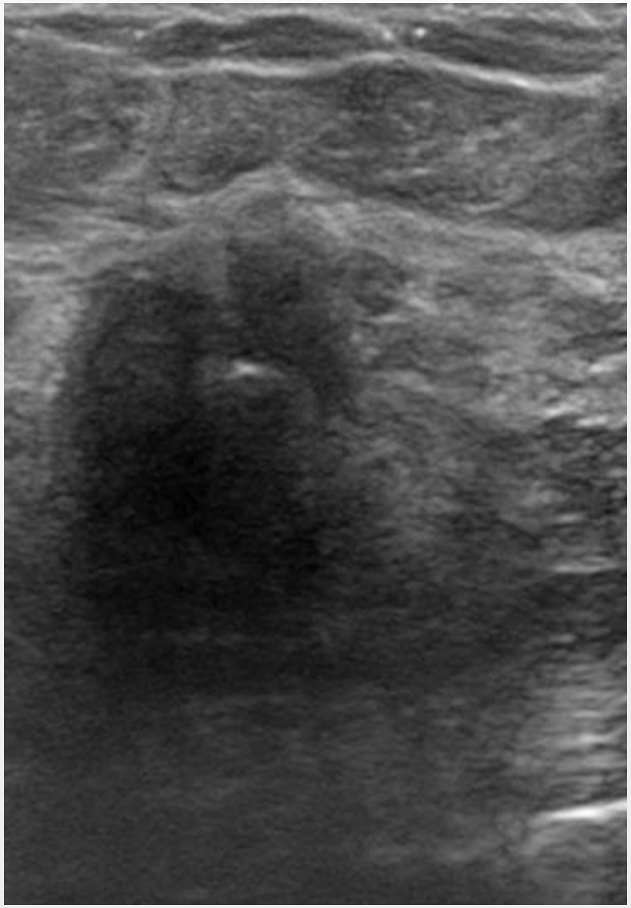
Initial Results: Simulated Data



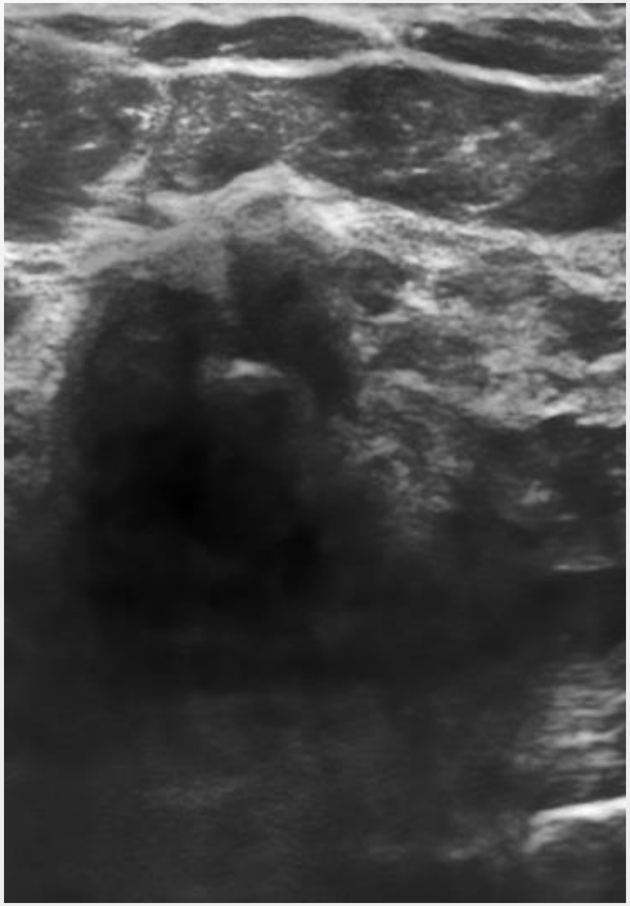
Average SNR improvement of 12 dB on simulated data with varying degrees of speckle noise added to the original



Initial Results: Clinical Data



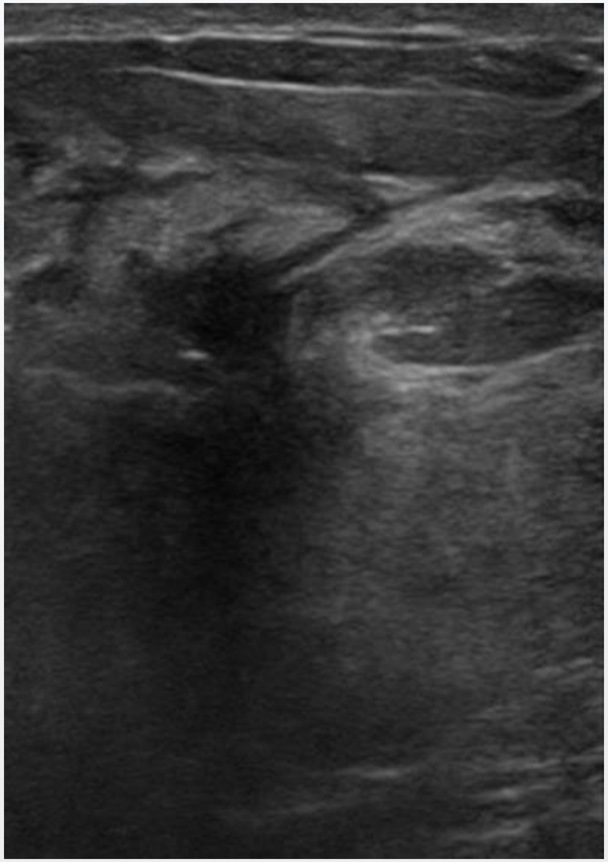
Original Ultrasound
(Siemens Acuson S2000)



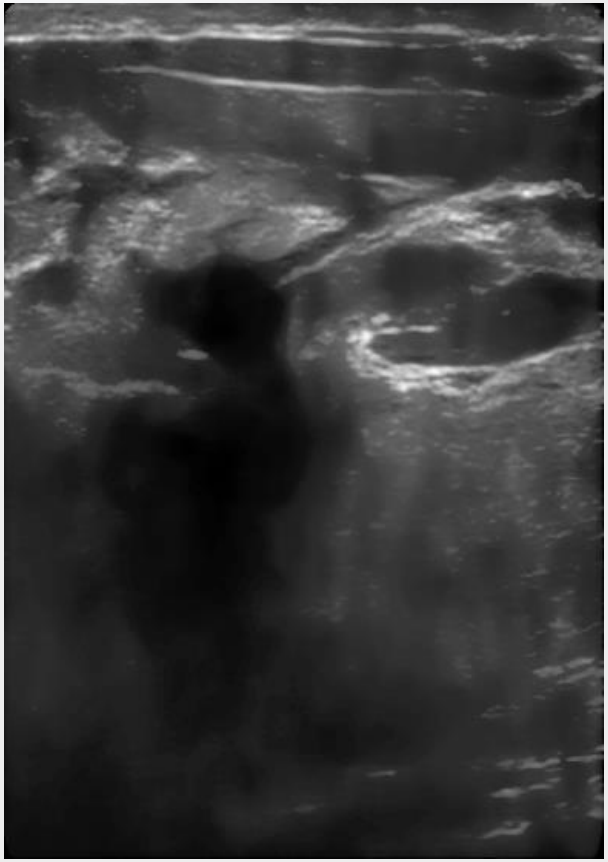
ClearView Post-Processed

Palpable 2 cm ill-defined mass on right breast
BI-RADS®: 5
Highly suggestive of malignancy
Calcifications found on mammogram
Breast Density: 3
Nodular & Heterogeneously Dense limiting internal visibility
Initial US did not demonstrate a suspicious finding – second US and/or MRI recommended
Biopsy: Positive
Invasive lobular carcinoma
ClearView image provides clearer lesion borders, details and small structures that appear to be calcifications

Initial Results: Clinical Data



Original Ultrasound
(Siemens Acuson S2000)

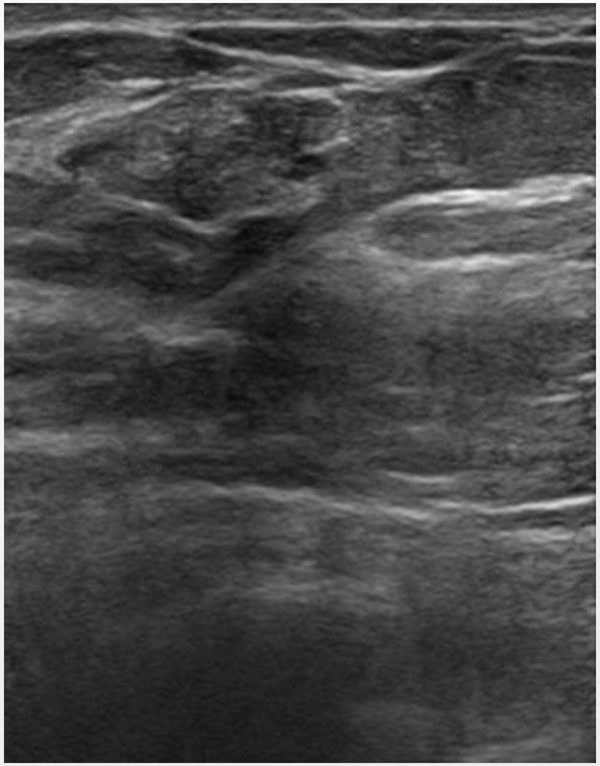


ClearView Post-Processed

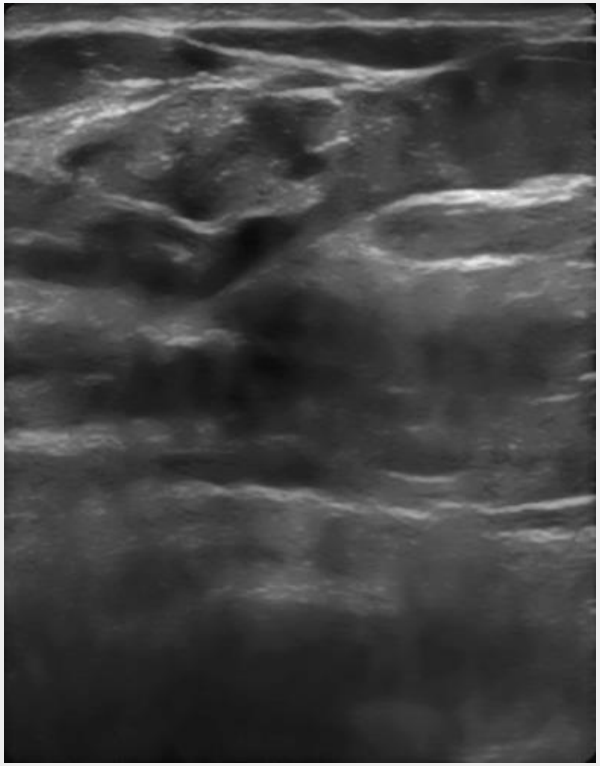
Palpable 2.1cm mass on left breast and 1.7 cm mass on right breast
BI-RADS®: 5
Highly suggestive of malignancy
Calcifications found with lesion on right breast
Breast Density: 3
Biopsy: Positive
Invasive ductal carcinoma with calcifications
Image of lesion on right breast pre-core

ClearView image provides clearer lesion borders, details and small structures that appear to be calcifications

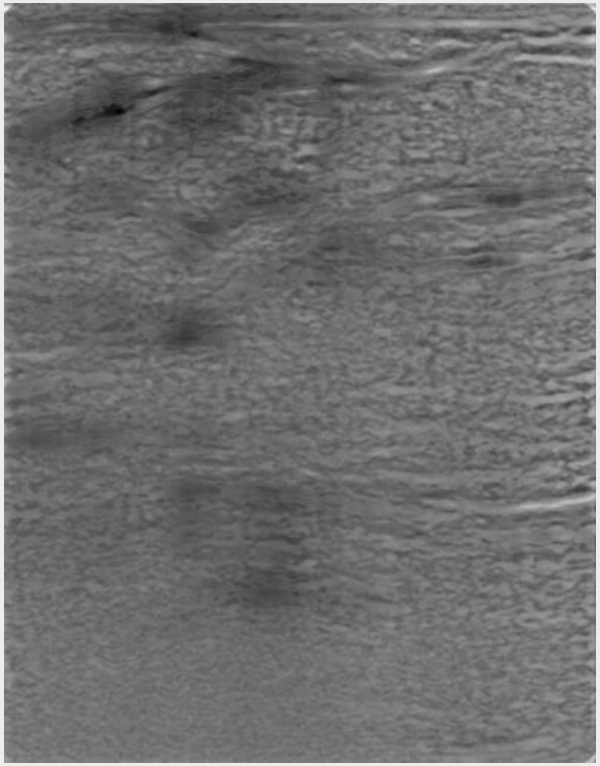
Initial Results: Clinical Data



Original Ultrasound
Siemens Acuson S2000



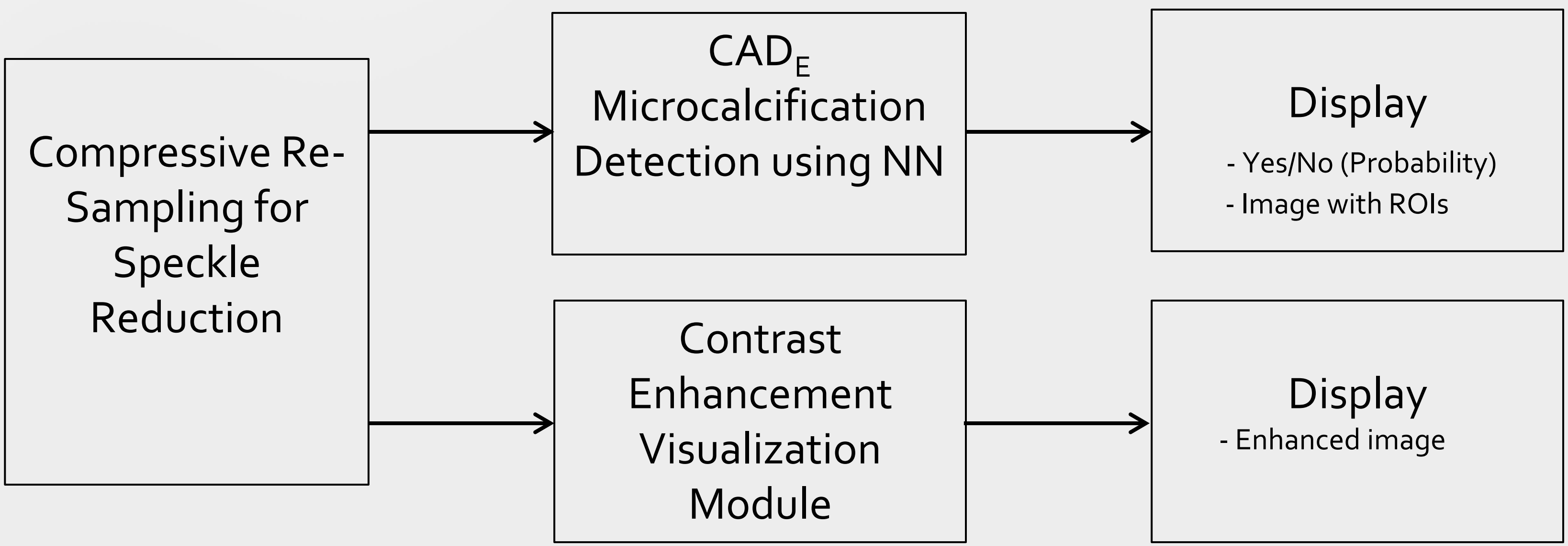
ClearView Post-Processed



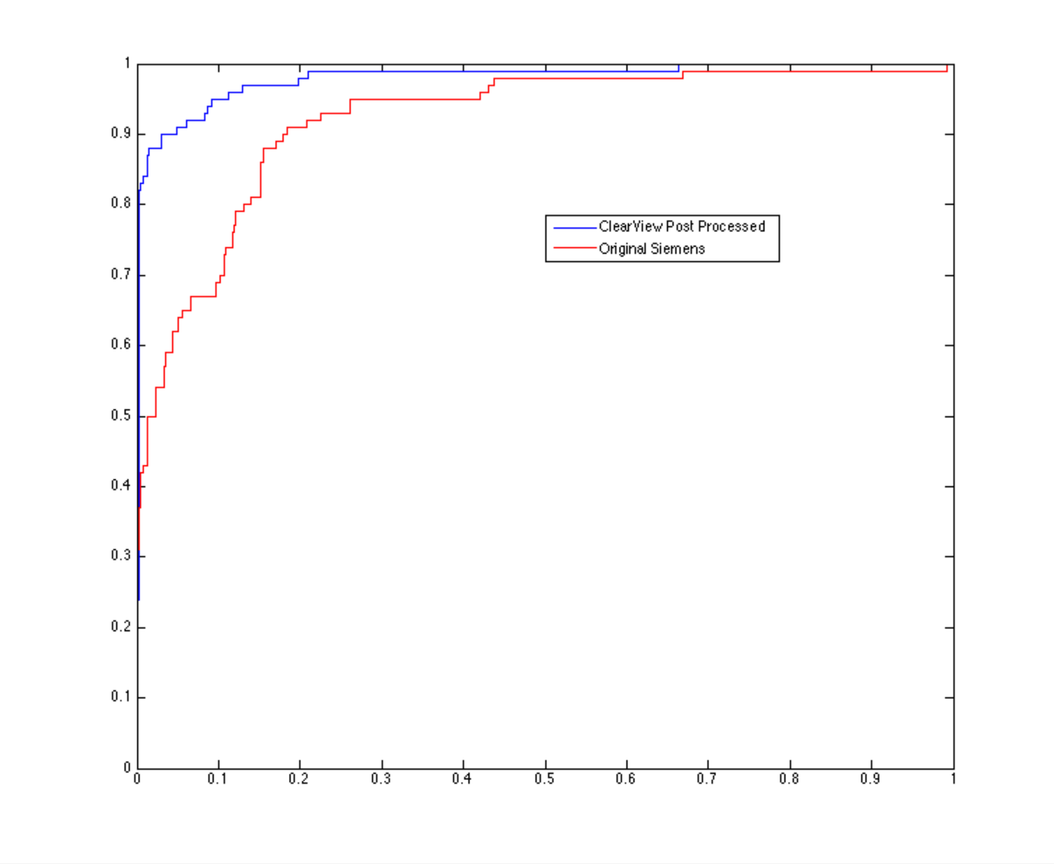
Noise removed from original

Initial Results: Recognition Improvement

- Apply the Compressive Re-Sampling (CRS) Method as a preprocessor to a CAD (Computer Aided Diagnostic) system to determine whether it improves recognition performance
- Detection of microcalcifications using Neural Networks
- Roc curves were generated to determine the NN's ability to detect microcalcifications on the original (Siemens) images and the ClearView post-processed images



Initial Results: RoC Curve for CAD using Compressive Re-Sampling



	Sensitivity at 0.5% FAR
Original (Siemens)	40%
ClearView Post-processed	82%

Thank You

Questions