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Intrinsic Tradeoffs in Multi-covariate Imaging of Sub-resolution Targets

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Abstract

Multi-covariate Imaging of Sub-resolution Targets (MIST) is an estimation-based method of imaging the statistics of diffuse scattering targets. MIST estimates the contributions of a set of covariance models to the echo data covariance matrix. Models are defined based on a spatial decomposition of the theoretical transmit intensity distribution into on-axis and off-axis contributions, delineated by a user-specified spatial cutoff. We define this cutoff as the region of interest width (ROI width). In our previous work, we selected the ROI width as the first zero crossing separating the mainlobe from the sidelobe regions. This paper explores the effects of varying two key parameters on MIST image quality: (1) ROI width and (2) the degree of spatial averaging of the measured echo data covariance matrix. These results demonstrate a fundamental tradeoff between resolution and speckle texture. We characterize MIST imaging performance across these tunable parameters in a number of simulated, phantom, and *in vivo* liver applications. We consider performance in noise, fidelity to native contrast, resolution, and speckle texture. MIST is also compared to varying levels of spatial and frequency compounding, demonstrating quantitative improvements in image quality at comparable levels of speckle reduction. In an *in vivo* example, optimized MIST images demonstrated 20.2% and 13.4% improvements in contrast-to-noise ratio over optimized spatial and frequency compounding images, respectively. These results present a framework for selecting MIST parameters to maximize speckle signal-to-noise ratio without an appreciable loss in resolution.

Keywords

Ultrasound; spatial covariance; beamforming; estimation; optimization

I. Introduction

OPTIMIZATION in medical ultrasound imaging takes many forms. Each step of the image formation pipeline is subject to many parameter choices and tradeoffs to maximize image quality, from transmit beam design to signal processing and image display. Design optimization spans hardware development to system architecture and software algorithms, balancing competing effects such as performance, efficiency, and cost.

On the front end, manufacturers invest significant resources to optimize transmit sequencing and beam design. Design choices include transmit apodization, focal zone selection, and beam grid density. Other considerations include the selection of a transmit center frequency, and the use of fundamental or harmonic imaging modes [1], [2].

On the back end, beamformed image data are subject to numerous post-processing algorithms, the most common of which involve speckle reduction. While speckle reduction methods used by scanner manufacturers are largely proprietary, approaches have been detailed in the literature using a variety of algorithms [3]-[8], which are subject to a bevy of optimization parameters such as window selection, iteration count, and thresholding and smoothing parameters. Other features of post-processing algorithms may include edge or contrast enhancement, time gain compensation or dynamic range alterations, temporal averaging, and other filtering methods to improve the quality of the output image [9]-[11].

Between transmit sequencing and image post-processing lies the receive beamformer, which converts the raw, radiofrequency (RF) echoes received by the transducer to a spatial map of target echogenicity. This is typically accomplished through a series of time delays to account for path length differences between the echo source and the array elements, using a simple geometric model and an assumed speed of sound in the medium. The time-delayed echo data are summed across the receive aperture to form a beam. This process constitutes conventional delay-and-sum beamforming. Typical receive beamforming optimization choices may include receive apodization or aperture growth to maintain a fixed f-number ($f/\#$) through depth.

Beyond conventional delay-and-sum beamforming, many advanced methods have been proposed to improve image quality. These algorithms vary in both complexity and efficacy, with various goals including speckle reduction, resolution enhancement, improved target detectability, and/or the general minimization of clutter or other image artifacts. Many require the selection of one or more tunable parameters to modulate the performance of the algorithm.

A classical example is receive spatial compounding, which seeks to improve speckle texture through the incoherent summation of sub-images formed from overlapping sub-arrays within the receive aperture [12]-[14]. Under this framework, the user must select the number, size, and weighting of the sub-apertures, informed by the predicted decorrelation of the speckle pattern between sub-images. This presents a tradeoff between speckle reduction and image resolution.

Frequency compounding incoherently sums a set of partially-correlated sub-images formed from different frequencies in the signal bandwidth. This is accomplished by applying a bandpass filter to specific portions of the received signal bandwidth to form each sub-image [15]. Tunable parameters include the number, bandwidth, and overlap of the frequency bins.

Another popular beamforming method in the literature is the minimum variance beamformer [16], [17], which seeks to minimize the contributions of off-axis interferers through the adaptive selection of array weights. This is accomplished through a constrained optimization which effectively nulls the receive beam pattern in the direction of off-axis interference sources. A key feature of this algorithm is the estimation of the echo data covariance matrix. To achieve a well-conditioned estimate, the receive aperture is typically divided into sub-arrays of length L , over which an average covariance matrix is calculated to be used in the optimization. These covariance estimates may also be averaged over a small number of temporal samples. Large values of L improve resolution at the expense of speckle brightness and uniformity, representing a fundamental tradeoff in algorithm design [18].

Other methods employ estimates of spatial coherence in the image formation process, where spatial coherence describes the similarity of signals across the aperture at a given point in time [19], [20]. Most coherence-based imaging methods present a fundamental tradeoff between (1) resolution and contrast and (2) speckle texture. Examples with tunable parameters include the phase coherence factor (PCF) and sign coherence factor (SCF) [21], the generalized coherence factor (GCF) [22], and short-lag spatial coherence (SLSC) imaging [23]. The filtered-delay multiply and sum algorithm (F-DMAS) [24] has also recently been modified to incorporate only a short-lag region [25].

The PCF and SCF apply weights to the delay-and-sum B-Mode image pixels. The weights are calculated from phase variations in the aperture data and modulated by tunable parameters γ and p , respectively, to adjust the sensitivity of the metric to out-of-focus signals. The GCF also applies weights to the B-Mode image pixels, determined by a ratio of the coherent portion of the echo data to the total signal power based on a specified lateral spatial frequency cutoff, M_0 . SLSC, by contrast, calculates image pixels directly from correlations of the echo data between pairs of array elements, integrated up to a maximum lag in the receive aperture, a parameter chosen by the user. Similarly, short-lag F-DMAS forms images from the pairwise multiplication and summation of array signals up to a maximum lag, which is followed by a signed square root operation.

Recently, our group introduced Multi-covariate Imaging of Sub-resolution Targets, or MIST [26]-[28], an estimation-based method to image the statistics of diffuse scattering targets. MIST seeks to quantify the contributions of a set of covariance models to the measured echo data covariance matrix. The models are defined based on a spatial region of interest which delineates on-axis from off-axis scattering sources. MIST includes a number of tunable parameters, notably the region of interest size, as well as the degree of spatial averaging used in the covariance estimate.

Our previous work employed a fixed set of MIST covariance models delineated by the first zero crossing of the predicted narrowband point spread function at the transmit focal depth

[26]. Images were typically formed using a small degree of spatial averaging (one wavelength in range). While MIST images formed with these parameters have demonstrated improved image quality over conventional methods, the effects of modulating these parameters have not been characterized.

The goal of this paper is to analyze the effects of (1) region of interest size and (2) the degree of spatial averaging on MIST speckle texture, resolution, and conventional lesion detectability metrics. In Section II, relevant theory is reviewed and a formal definition of MIST tunable parameters is presented. Methods are described in Section III. Results are presented in Section IV and discussed in Section V. Conclusions are presented in Section VI.

II. Theory

A. Multi-covariate Imaging of Sub-resolution Targets

Multi-covariate Imaging of Sub-resolution Targets, or MIST, is an image formation method that estimates on-axis contributions to the echo data covariance matrix, based on a model of the statistical properties of diffuse scattering targets [26]. MIST relies on a key assumption: the covariance of backscattered echoes from diffuse targets is the superposition of covariances from distinct spatial regions in the field. This relationship is given by [27]:

$$\mathbf{R} = \sum_{p=1}^P \alpha_p^2 \mathbf{R}_p, \quad (1)$$

where the covariance $\mathbf{R}$ is represented by a superposition of constituent covariance matrices $\mathbf{R}_p$ each weighted by a scalar variance α_p^2 . The full derivation leading to Eq. (1) is presented in [27], however, for the purposes of this analysis, it suffices to note that the measured covariance can be decomposed into P constituents corresponding to distinct spatial regions in the image and additive noise sources.

MIST applies an estimation-based approach to image formation, seeking to quantify the contributions of each model $\mathbf{R}_p$ to the measured covariance $\hat{\mathbf{R}}$. Images are formed from the model corresponding to on-axis echoes. The estimator is derived in full in [26]; however, a brief overview is presented below.

For an M -channel array, the complex array data at time sample t are given by the $M \times 1$ vector $\mathbf{x}[t]$. We will assume $\mathbf{x}[t]$ have been time-delayed using conventional dynamic receive focusing. The estimated covariance matrix is given by:

$$\hat{\mathbf{R}}[t] = \frac{1}{T} \sum_{\tau=-T/2}^{T/2} \mathbf{x}[t+\tau] \mathbf{x}^H[t+\tau], \quad (2)$$

where the $M \times M$ covariance matrix at time sample t is given by $\hat{\mathbf{R}}[t]$ and the conjugate transpose operation is given by (H) . To improve the stability of the estimate, measurements may be averaged over a small axial window (T), which is typically on the order of a wavelength. To simplify notation, we consider the covariance at a single sample, such that $\hat{\mathbf{R}} = \hat{\mathbf{R}}[t]$.

Following the model of Eq. (1), the covariance $\mathbf{R}$ is described as a superposition of P constituent covariance models ($\mathbf{A}_i$). A noise term ($\mathbf{N}$) is also included to model uncertainty in the observation. This is given by:

$$\mathbf{R} = \sum_{i=1}^P \alpha_i^2 \mathbf{A}_i + \mathbf{N}, \quad (3)$$

where each covariance model $\mathbf{A}_i$ is weighted by scalar variance α_i^2 .

MIST estimates the weights α_i^2 . This is accomplished using a least squares estimator, given by:

$$\hat{\alpha}_{ls}^2 = \arg \min_{\alpha^2} \left\| \hat{\mathbf{R}} - \sum_{i=1}^P \alpha_i^2 \mathbf{A}_i \right\|_F^2 \text{ subject to } \alpha^2 \geq 0, \quad (4)$$

where (F) represents the Frobenius norm [29]-[31]. The vector of estimated variances for models $\mathbf{A}_i$ is given by $\hat{\alpha}_{ls}^2$.

The models $\mathbf{A}_i$ are typically selected as the predicted (1) mainlobe and (2) sidelobe contributions to the speckle covariance, and (3) an identity matrix representing incoherent noise [26], [27]. The estimation described by Eq. (4) is performed on a pixel-by-pixel basis, where final image pixels correspond to the magnitude of the on-axis mainlobe estimate: $|\alpha_1(x, z)|$.

MIST has demonstrated significant improvements in image quality over conventional B-Mode, including consistent gains in contrast-to-noise ratio (CNR) and speckle signal-to-noiseratio (SNR), while preserving native contrast and resolution [26]. This has been demonstrated under a number of conventional and synthetic aperture focusing configurations [28].

B. Tunable Parameters in MIST

The conventional definition of the speckle covariance models in MIST correspond to the nominal mainlobe and sidelobes of the beam profile, delineated by the first zero crossing of the predicted narrowband intensity distribution [26]. While this is an intuitive choice for a cutoff, it may be beneficial to adjust the inside-outside cutoff region to restrict or expand the look direction. A choice in the inside-outside cutoff will dictate the covariance models $\mathbf{A}_i$ in Eq. (4).

Accordingly, we define the cutoff between the inside and outside regions as the region of interest width (or *ROI width*). This is mathematically defined as the lateral distance from beam center to the cutoff point, with units of $\lambda z/D$, where λ is the wavelength, z is the depth, and D is the azimuthal aperture width. At the transmit focus, the zero-crossings of the predicted narrowband intensity profile occur at integer multiples $\lambda z/D$, such that the conventional MIST model uses an ROI width of 1.0. A graphical description of ROI width is

located in Fig. 1, where ROI widths of 0.5, 1.0, and 2.0 are compared, showing the variation of predicted correlation and covariance functions of the inside and outside regions.

Additionally, spatial averaging is typically incorporated in the covariance estimate, as described in Eq. (2). Previous results have demonstrated MIST with a kernel size (T) of one wavelength (1λ). However, more or less spatial averaging may be preferable, as a smaller T may maximize axial resolution, but with a noisier estimate of the sample covariance. Conversely, increased spatial averaging (larger T) may improve the conditioning of the covariance estimate, but at the expense of axial resolution. We define the kernel size as the axial range T over which covariance estimates are averaged to form each MIST image pixel.

III. Methods

Simulation and experimental studies were performed to evaluate MIST performance across the parameter space of ROI width and axial kernel size, and to compare MIST with conventional beamforming methods involving similar tradeoffs.

A. Simulation Studies

Field II [32], [33] was used to simulate a number of imaging targets. For all simulations, the transducer was a 64-element, 3 MHz linear array with $300\ \mu\text{m}$ pitch and 70% fractional bandwidth. Rectangular apodization was used on both transmit and receive. The transmit focus was set to 50 mm. Simulations were performed at 120 MHz. Radiofrequency (RF) echo data were collected and downsampled to 20 MHz before processing. Speckle-generating targets contained 20 scatterers per resolution cell.

1) Anechoic Cyst Target: The first simulated target consisted of an anechoic cylinder of 10 mm diameter at 50 mm depth in a $80 \times 30 \times 50\ \text{mm}$ ($x \times y \times z$) speckle-generating background. Five speckle realizations were simulated. MIST images were formed as a function of ROI widths ranging from (0.1 – 5.0) and axial kernel sizes of 0, 1, and 2λ . Additionally, white Gaussian noise was bandpass filtered to the transducer bandwidth, and added to the unfocused RF data before processing to simulate a set of specified channel signal-to-noise ratios (SNRs) between -40 and $+40\ \text{dB}$.¹

2) Edge Phantom Targets: A set of anechoic edge phantoms were simulated, in which a speckle-generating region of diffuse scatterers was placed next to an anechoic region. Simulations were performed for lateral and axial edge cases. For the lateral phantom, the edge was located at $x = 0\ \text{mm}$, where the scattering region measured $25 \times 10 \times 50\ \text{mm}$ ($x \times y \times z$) in size. For the axial phantom, the edge was located at $z = 50\ \text{mm}$, where the scattering region measured $50 \times 10 \times 25\ \text{mm}$. For each target, 10 speckle realizations were simulated. An example of the lateral edge phantom is shown in Fig. 4.

Three sets of images were formed for each simulated data set: (1) MIST using ROI widths of (0.1 – 2.0) and (0, 1, 2) λ axial averaging, (2) receive spatial compounding [12]–[14], and (3)

¹Channel SNR was defined as the ratio between the root-mean-square (RMS) echo amplitude of a speckle generating region at the focal depth and the RMS amplitude of the noise. Previous work by our group has demonstrated channel SNR values encountered *in vivo* typically fall within $(-20, +20)\ \text{dB}$ [34].

frequency compounding [15]. For each image, the average lateral or axial profile (depending on phantom type), was calculated over a 10 mm window. For the lateral edge, the window was defined between $z = (45, 55)$ mm at $x = 0$ mm. For the axial edge, the window was defined between $x = (-5, 5)$ mm at $z = 50$ mm. Lateral and axial resolution were defined as the distance from the known phantom edge to the -12 dB cutoff of the average lateral or axial profile, respectively. Speckle SNR and dropout rate (defined as the fraction of image pixels equal to zero) were calculated in a 1×1 cm region of interest at the transmit focus in the speckle generating region of the lateral edge phantom.

B. Phantom Studies

A Verasonics Vantage 256 (Verasonics, Inc., Kirkland, WA, USA) and a P4-2v phased array (64 elements, $300 \mu\text{m}$ pitch) were used to acquire echo data from number of cylindrical lesion targets in a tissue mimicking phantom (Model ATS 549, CIRS, Inc., Norfolk, VA, USA). Pulse inversion harmonic images were acquired using a 2.23 MHz center frequency on transmit, and a 4.46 MHz center frequency on receive. The sequence consisted of 121 transmit beams with 0.5° spacing (60° sector). RF echo data were collected at a sampling frequency of 17.9 MHz. Five speckle realizations of each target were captured by physically translating the transducer in elevation (approximately 1 cm between each capture) while keeping the same cylindrical targets in the field of view.

1) Native Contrast Targets: Data were collected from hypo- and hyperechoic cylindrical targets each with a diameter of 10 mm and manufacturer-specified native contrasts of -15 , -6 , $+6$, and $+15$ dB. The transmit focus was set to 40 mm ($f/2$). B-Mode images and MIST images with ROI widths of $(0.1-2)$ and 1λ axial averaging were formed.

2) Anechoic Targets: Data were collected from anechoic echoic cylindrical targets with 4 and 6 mm diameters, with a transmit focus at 60 mm ($f/3$). Three sets of images were formed: (1) MIST using ROI widths of $(0.1 - 2)$ and axial averaging of $(0, 1, 2)\lambda$, (2) receive spatial compounding, and (3) frequency compounding.

C. In Vivo Studies

The Verasonics Vantage scanner and a C5-2v curvilinear array (128 elements, $508 \mu\text{m}$ pitch) were used to collect RF echo data from the liver of a healthy male volunteer, in a protocol approved by the Duke University Institutional Review Board. A pulse-inversion harmonic sequence was used with a 2.36 MHz transmit center frequency and a 4.72 MHz receive center frequency. The transmit focus was 85 mm. Three sets of images were formed: (1) MIST using ROI widths of $(0.1 - 2)$ and axial averaging of $(0, 1, 2)\lambda$, (2) spatial compounding, and (3) frequency compounding.

D. Signal Processing and Image Formation

1) Focusing: The RF echo data were time-delayed using conventional dynamic receive processing to generate focused channel data. The focused channel data were then demodulated and downsampled to form baseband in-phase and quadrature (I/Q) data at a sampling frequency of 15 MHz.

2) Image Formation:

a) MIST Images: The MIST estimator was formulated incorporating three covariance models, corresponding to (1) the mainlobe and (2) sidelobe regions of the narrowband intensity profile at the focus and (3) an identity matrix to represent incoherent acoustic clutter, consistent with the methods of [26]. The mainlobe and sidelobe regions were segmented according to the specified ROI width, and the axial kernel was implemented by substituting for T in Eq. (2).

b) Receive Spatial Compounding: Spatial compounding images were formed by dividing the receive aperture into N sub-apertures of 50% overlap, whose images were incoherently compounded and N ranged from (1 – 32) [12]-[14].

c) Frequency Compounding: Frequency compounding images were formed by dividing the received signal bandwidth into N frequency bins with 50% overlap, whose images were incoherently compounded and N ranged from (1 – 16) [15].

E. Performance Metrics

Image quality was assessed using the following performance metrics: contrast (C), contrast-to-noise ratio (CNR), speckle signal-to-noise ratio (SNR), generalized contrast-to-noise ratio (gCNR) [35], resolution, and dropout rate. These are given by:

$$C = 20 \log_{10} \left(\frac{\mu_T}{\mu_B} \right), \quad (5)$$

$$CNR = \frac{|\mu_T - \mu_B|}{\sqrt{\sigma_T^2 + \sigma_B^2}}, \quad (6)$$

$$\text{Speckle SNR} = \frac{\mu_B}{\sigma_B}, \quad (7)$$

$$\text{gCNR} = 1 - \int_{-\infty}^{\infty} \min\{p_o(x), p_i(x)\} dx. \quad (8)$$

Mean and variance are given by μ and σ^2 , respectively, where T represents the target and B represents the background region of interest (ROI). For gCNR, $p_o(x)$ and $p_i(x)$ are the histograms of pixels measured in the background and target regions, respectively. Resolution was defined as the distance from the known phantom edge to the –12 dB cutoff of the average lateral or axial profile, respectively. Dropout rate was defined as the fraction of image pixels equal to zero in the background ROI.

IV. RESULTS

A. Simulation Studies

1) Anechoic Cyst Target: B-Mode and MIST images of the noise-free, simulated anechoic cyst target are shown in Fig. 2. MIST images (1λ) are shown for selected ROI widths between 0.2 and 5.0. At small ROI widths, images are characterized by a high rate of image dropouts, but with preferable edge definition. Dropouts occur when the constrained least squares estimator of Eq. (4) outputs a zero value for the on-axis, mainlobe estimate (α_1^2). As ROI width is increased, the speckle texture improves significantly, but at the expense of reduced edge definition. As ROI width is increased beyond 0.8, sidelobe effects are written into the lesion center.

Statistics of the MIST images are shown at the bottom of Fig. 2, plotted as a function of ROI width, with separate lines indicating the degree of spatial averaging. Contrast initially peaks, but decreases significantly as ROI width is increased, which may be attributed to increased sidelobe write-in to the lesion center. CNR, speckle SNR, and gCNR all improve with increasing ROI width, reaching an asymptote for ROI widths between 0.7 and 1.0. An increased degree of spatial averaging significantly improves the speckle SNR, which may be the primary factor behind the improved detectability described by CNR and gCNR. Across kernel sizes, the asymptote of the MIST CNR, speckle SNR, and gCNR exceed that of B-Mode. Contrast is increased relative to B-Mode for ROI widths below approximately 1.5.

B-Mode and MIST data from targets with noise added are shown in Fig. 3. Sample B-Mode and MIST images at channel SNR values of -12 , 0 , and $+12$ dB are shown in Fig. 3a. In the presence of noise, MIST images demonstrate similar visual trends as the noise-free case, as the rate of image dropouts is reduced with increasing ROI width while edge definition is gradually reduced. Visually, these trends appear less pronounced in the presence of increasing noise (-12 dB SNR).

The corresponding statistics are presented in Figs. 3b and 3c. Fig. 3b depicts image metrics as a function of ROI width, where each line indicates a specific channel SNR. All metrics are maximized in the high-SNR case ($+12$ dB), demonstrating similar trends to the statistics in Fig. 2. Conversely, image metrics are plotted as a function of channel SNR in Fig. 3c, where each line indicates a specific ROI width. In general, all metrics are maximized at the highest channel SNR ($+40$ dB), consistent with the results of Fig. 3 in [26]. Differences due to ROI width are most pronounced at smaller values such as 0.2 and 0.5 . Contrast generally decreases with increasing ROI width, with the exception of the 0.2 case, where the high rate of image dropouts decreases contrast relative to the 0.5 case.

2) Edge Phantom Targets: Sample images of the lateral edge phantom targets are shown in Fig. 4, visually demonstrating a resolution vs. texture tradeoff of increasing ROI width. At a small ROI width (0.5), the edge is well-defined, but with noticeable image dropouts. Conversely, as ROI width is increased, speckle texture is improved, but edge definition is reduced.

Statistics measured from the lateral and axial edge phantoms are shown in Fig. 5. Speckle SNR and dropout rate for MIST images as a function of ROI width and kernel size are shown on the left. Consistent with the results of Fig. 2, speckle SNR increases with increased ROI width, reaching an asymptote between (0.7 – 1.0), with proportional increases based on kernel size. Dropout rate is initially high (approximately 40%) at low ROI widths, but decreases to zero in a similar range, with the highest rate of image dropouts in the 0λ case. B-Mode images demonstrate constant speckle SNR at 1.91, and a dropout rate of 0.

Lateral resolution worsens with increasing ROI width, and is independent of kernel size, eclipsing that of B-Mode at approximately (0.7 – 0.8). Axial resolution is relatively insensitive to ROI width, but worsens with increased axial averaging. The lateral resolution of 0λ MIST is approximately equivalent to that of B-Mode.

Lateral and axial resolution, respectively, are plotted against speckle SNR in Fig. 6. The axes of each ellipse represent the standard deviation of each measurement across 10 speckle realizations. On the left, MIST is evaluated against receive spatial compounding. For a comparable lateral resolution, MIST demonstrates a higher speckle SNR. The asymptotes of lateral resolution and speckle SNR in Fig. 5 are noted by the overlap of MIST ellipses after the ROI width reaches approximately 0.8.

On the right, MIST axial resolution and speckle SNR is compared to frequency compounding. Similarly to the lateral resolution case, MIST achieves a higher speckle SNR than frequency compounding at a comparable axial resolution. As demonstrated in Fig. 5, MIST axial resolution is worsened with increasing axial kernel size, but is relatively insensitive to selection of ROI width. At a kernel size of 0λ , MIST axial resolution is approximately equivalent to that of B-Mode (i.e. frequency compounding with one frequency bin).

B. Phantom Studies

B-Mode and MIST images of the native contrast targets for selected ROI widths are shown in Fig. 7. As with the simulation results, small ROI widths yield high rates of image dropouts, which decrease as ROI width is increased. This is consistent across targets of varying echogenicity relative to the background. The measured contrast of each target, averaged across five speckle realizations, is plotted on the right. From top to bottom, the manufacturer-specified contrast values were listed as +15, +6, -6, and -15 dB. However, the average B-Mode contrast values were measured as +13.9, +8.7, -2.4, and -11.8 dB, respectively. Across targets, MIST contrast asymptotes to the measured B-Mode contrast as ROI width is increased. High rates of image dropouts at small ROI widths appear to slightly skew these measurements.

MIST images of the hypoechoic targets and anechoic targets as a function of axial kernel size are presented in Fig. 8. The ROI width was 1.0 for all images. As kernel size is increased from 0λ to 2λ , speckle texture is noticeably smoothed, but at the expense of axial resolution and reduced lesion conspicuity. This is particularly noticeable in the center of the anechoic targets: the clutter in the 0λ images becomes more distributed among neighboring pixels.

Images of the anechoic phantom targets are shown in Fig. 9. At the top, MIST images (1λ) are shown for selected ROI widths, demonstrating qualitative improvements in speckle SNR with reduced contrast as ROI width is increased. The center row shows images of receive spatial compounding, with sub-aperture sizes ranging from (1 – 32). The bottom row shows images of frequency compounding, with the number of frequency bins to be compounded ranging from (1 – 16). Both spatial and frequency compounding show an improvement in speckle texture at the expense of contrast, as well as lateral and axial resolution, respectively.

Image statistics for the anechoic phantom targets are shown in Fig. 10, with columns representing the statistics of each method. Similar to the simulation results (Fig. 2), MIST contrast decreases with increasing ROI width, while CNR, SNR, and gCNR increase and reach an asymptote in the (0.7 – 1.0) range. Larger axial kernel sizes appear to reduce contrast slightly, likely due to worsened axial resolution at the edges of the region of interest used to measure the statistics. Spatial and frequency compounding demonstrate similar trends: a gradual decrease in contrast, offset by improvements in speckle SNR, leading to general improvements in CNR. The gCNR of spatial compounding appears to asymptote, while frequency compounding reaches a peak, and decreases. This may be due to the severe losses in axial resolution, visible in the bottom right plot of Fig. 9.

C. In Vivo Studies

In vivo liver images, presented in Fig. 11, show large vasculature of approximately 10 mm in diameter located at 87 mm depth. MIST images of varying ROI width are visually compared to both spatial and frequency compounding images with increasing sub-aperture and frequency bin count, respectively. MIST images demonstrate a qualitative improvement in background speckle texture with increasing ROI width, while the vessel contrast is reduced. Spatial and frequency compounding show progressively smoother speckle texture at the expense of contrast. Axial resolution is noticeably degraded in the 8- and 16-bin frequency compounding images.

The statistics measured from the images of Fig. 11 are plotted in Fig. 12. MIST images demonstrate similar trends to previous results: increased ROI width leads to a quantitative reduction in contrast, while CNR, speckle SNR, and gCNR increase, and asymptote around an ROI width of 0.7. Spatial and frequency compounding demonstrate a progressive loss in contrast with increased sub-aperture and frequency bin count, respectively, while speckle SNR continues to improve. These effects result in peaks in the CNR and gCNR plots for both methods. For spatial compounding, these appear at approximately 7 sub-apertures. For frequency compounding, the maxima are more difficult to distinguish, but appear in the range of (5 – 8) frequency bins.

MIST 1λ and 2λ exceed spatial and frequency compounding in terms of contrast, CNR, and gCNR, whereas MIST 0λ asymptotes at a comparable level to the peak values of the other methods. The peak CNR of MIST 2λ exceeded those of spatial and frequency compounding by 20.2% and 13.4%, respectively. For MIST 1λ , the increases were 11.7% and 5.3%. For the x -coordinate of the CNR maxima (ROI width, sub-aperture count, or frequency bin count, respectively), MIST 2λ contrast exceeded spatial and frequency compounding

contrast by 5.7 and 5.3 dB, respectively. At the same x -coordinate, all three methods have comparable speckle statistics.

V. Discussion

A. MIST Image Characteristics: Tunable Parameters

MIST images were characterized as a function of ROI width and axial kernel size, indicating a fundamental tradeoff of speckle texture vs. resolution. This was consistent between linear, curvilinear, and phased array geometries. MIST images formed using smaller ROI widths yielded a high rate of image dropouts, which occur when the constrained least squares estimator of Eq. (4) outputs a zero value for the on-axis, mainlobe estimate (α_1^2). The dropouts may be a result of a mismatch between the model covariance and the measured covariance, when the estimator attributes the majority of energy to one of the other models (sidelobes or incoherent noise in this case). This preferentially occurs in the darker pixels within the speckle pattern, which have a lower coherence than their brighter counterparts and vary substantially from the mainlobe covariance model (which becomes a more flat function as the ROI width is reduced).

In general, a small ROI width yielded the highest resolution, as measured quantitatively in the simulated edge phantoms, but at the expense of a high speckle variance and dropout rate. As ROI width was increased, resolution was reduced, but speckle SNR improved substantially, reaching an asymptote in most cases between ROI widths of 0.7 and 1.0. These results were consistent across simulated targets, phantom targets, as well as an *in vivo* liver example.

Similar results were observed for axial averaging. Increasing the axial kernel size significantly improved speckle SNR at the slight expense of contrast and edge definition. The larger kernel size consistently improved MIST CNR and gCNR across targets. In particular, the increase from 0λ to 1λ yielded a substantial increase in speckle SNR with a loss of resolution barely noticeable in Fig. 8. These results suggest that some degree of spatial averaging may be preferable. A reasonable choice in general may be 1λ ; however, the optimal kernel size may vary as a function of the target size (smaller targets may have unacceptable visibility with large kernel sizes). Recent work by our group has demonstrated the optimal degree of averaging achieved by spatial compounding may be patient- and/or task-specific [36]; similar results might be expected for MIST kernel size.

These results provide a framework for MIST parameter selection. An optimization criterion might be to maximize contrast and speckle SNR, while mitigating losses in resolution. A reasonable ROI width may then be selected as the smallest value which prevents dropouts (i.e. at or near the speckle SNR asymptote), but still maximizes contrast. These results suggest this range is typically between 0.7 and 1.0, generally smaller than the ROI width of 1.0 used in our earlier work [26], [28]. While these results were presented within the depth of field for focused transmissions, we expect these results to generalize to synthetic aperture focusing geometries as described in [28].

B. Comparison to Alternative Image Formation Methods

The plots of Fig. 6 display the resolution vs. texture tradeoff inherent to the choice in ROI width and kernel size. MIST was compared to both spatial and frequency compounding, and was shown to yield a higher speckle SNR at comparable lateral and axial resolution values, respectively. These results were generalized to imaging applications in the phantom and *in vivo* images in Figs. 9 and 11, respectively, in which MIST images of anechoic targets and liver vasculature were compared to spatial and frequency compounding images.

In the phantom target, spatial compounding moderately improved speckle texture, but at a noticeable loss in contrast. Similar trends were observable for frequency compounding; as the number of bins was increased, speckle SNR continued to improve while contrast and axial resolution were degraded substantially. Image statistics (Fig. 10) demonstrated improved MIST contrast, and gCNR. Speckle SNR was equal or higher in the frequency and spatial compounding images, which led to comparable CNR values.

Similar effects were observed in the *in vivo* liver. However, spatial compounding SNR did not asymptote as observed in the phantom. This may be a consequence of the complex scattering environment encountered *in vivo*, characterized by aberration and other image degradation effects not typically encountered in an imaging phantom. The image statistics (Fig. 12) demonstrated improved contrast, CNR, and gCNR of MIST over spatial and frequency compounding.

The results of Figs. 9 through 12 present an interesting discrepancy. In multiple cases, statistics such as CNR or gCNR reach an asymptote, while visually, an observer may notice clear differences in the images. In Figs. 9 and 10, this is evident in MIST: the image formed with an ROI width of 0.8 demonstrates noticeably better contrast than the 2.0 image. However, the CNR and gCNR are nearly identical. Similarly, the 16-bin frequency compounding image in both the phantom and *in vivo* examples is severely degraded relative to the 1-bin image (B-Mode). However, it possesses a higher average CNR, which appears at odds with the visual results. Looking at CNR alone, one might hypothesize aggressive frequency compounding may be a viable beamforming method, which would be at odds with the literature [13]. However, this degradation is captured by the gCNR, which reaches a peak and dips as more frequency bins are compounded.

In principle, MIST shares similar goals to the minimum variance (MV) beamformer, which seeks to suppress off-axis contributions to the echo data through the adaptive selection of array weights [16]-[18]. Despite these similarities, the MV approach does not involve a spatial decomposition of covariance matrices, and is primarily formulated around discrete interferers rather than the underlying statistical properties of backscatter. Like MIST, the MV approach presents a tradeoff between resolution and speckle texture as a function of parameter selection [18].

C. Limitations and Future Work

While this work explored two tunable parameters in MIST, there may be other parameters of interest to further improve image quality. One example might include the use of additional regions of interest (beyond a simple inside/outside cutoff). Windowing (or apodizing) the

regions of interest may be beneficial. More advanced covariance modeling may also present an opportunity for optimization, potentially accounting for broadband pulses, depth-dependent effects, or angular sensitivity. More sophisticated models of noise and clutter may also be beneficial.

Furthermore, the images presented in this work were not subjected to any post-processing, which may improve image quality across methods. It may be possible to design filtering methods to mitigate the dropout artifacts associated with small ROI widths.

The data in this work were collected without the use of transmit apodization, chosen for both simplicity and the familiarity of the triangular van Cittert-Zernike coherence curve [20]. However, most clinical scanners employ apodization to suppress sidelobe clutter at the expense of a slightly wider mainlobe. While this is undoubtedly beneficial in conventional B-Mode imaging, it is not clear if apodization presents similar tradeoffs in MIST. Given that MIST estimates both mainlobe and sidelobe scattering, deep suppression of sidelobe energy may hamper its ability to estimate the latter, which may reduce image quality. Likewise, it is possible that unconventional apodization schemes for B-Mode imaging may benefit MIST image quality. Characterizing the effects of transmit apodization on MIST image quality may be a target of future work.

A classical analysis of the performance of an estimator would include the characterization of bias and variance [29]. However, given that the MIST estimator is used to form images, the performance was evaluated in the image domain using the methods described in this paper, showing a tradeoff between resolution and speckle SNR. Previous work [26] and Fig. 7 have shown the estimator to be unbiased over a range of native echogenicities. For an unbiased estimator, the variance σ^2 is proportional to $1/\text{SNR}^2$, where SNR is defined by Eq. (7). We will leave to future work to analyze in detail how bias and variance may vary as a function of imaging parameters.

As with any beamforming method, image statistics alone do not provide definitive criteria for optimal image quality. Each of contrast, CNR, and speckle SNR provide valuable information; however, nonlinear steps in the beam- or imageforming process can lead to dynamic range alterations that can skew these metrics [37]. While gCNR is robust to nonlinear transformations, it also only considers histogram overlap as opposed to histogram separation. Thus while a target and background may not overlap (and thus have the same gCNR), their degree of separation may cause significant differences in the image. These differences may be minimized through choices in dynamic range and grayscale transfer curves.

It should also be noted that gCNR does not have a normal sampling distribution, such that values near the upper limit of 1 become tightly clustered. Accordingly, small differences in gCNR become more significant as the measured gCNR values approach 1. These differences may be easier to visualize when plotted on a logarithmic scale. Alternatively, a nonlinear transform to normalize these distributions may be appropriate for visualization or statistical analysis, analogous to a Fisher-z transform for Pearson's correlation coefficient [38].

Resolution is often characterized using the full width at half maximum (FWHM) of a coherent point target. However, MIST seeks to estimate the statistical properties of diffuse, speckle-generating targets, such that a coherent point target is not well accounted for in the modeling. The use of an edge of a speckle-generating target better reflects the estimator's resolution performance. However, point-like targets can be present in clinical imaging environments, and like many coherence-based methods, MIST is subject to a dark region artifact [39] near specular targets. These artifacts may complicate the image formation process. Addressing this issue through improved modeling or other signal or post-processing may be a target of future work.

A more comprehensive image quality analysis might incorporate resolution measurement into a detectability metric, such as an ideal observer approach (which would need to be modified to account for image formation methods that deviate from Rayleigh statistics) [40]. Most importantly, a full evaluation of image quality should involve trained readers accustomed to viewing and interpreting images for diagnostic purposes.

Though the goal of this work was to identify general parameters to be used prospectively for MIST image formation, it is also possible to iteratively determine an optimal ROI width and/or kernel size on a per-pixel basis, though this would increase the computational burden substantially. Efficient implementation strategies may also be a target of future work.

VI. Conclusion

MIST imaging performance was evaluated across two tunable parameters: (1) the lateral cutoff between the on- and off-axis covariance models and (2) the degree of axial spatial averaging, demonstrating a fundamental tradeoff between resolution and speckle texture. MIST images were evaluated across the parameter space, indicating a small degree of spatial averaging and a cutoff slightly narrower than the first zero crossing of the point spread function optimized image quality. MIST images across this parameter space were also comparatively evaluated against spatial and frequency compounding, demonstrating quantitatively improved speckle SNR at comparable resolution levels and improved image quality in phantom and *in vivo* applications. These results provide a framework for parameter selection in MIST.

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Biography

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Fig. 1:

Graphical description of MIST ROI width showing the transmit intensity, segmented into inside (red) and outside (blue) regions based on a specified cutoff (0.5, 1, and 2). Correlation and covariance plots of each region are shown for each example cutoff.

Fig. 2:

Simulated anechoic cyst images as a function of MIST ROI width, visually demonstrating the tradeoff between edge resolution and speckle texture. Contrast, CNR, speckle SNR, and gCNR are plotted on the bottom for B-Mode and MIST images with axial kernel sizes of (0, 1, 2) λ . Increasing ROI width reduces resolution and contrast, but improves CNR, speckle SNR, and gCNR. Error bars represent the standard deviation across 5 speckle realizations.

Fig. 3:

Simulated anechoic cyst images as a function of MIST ROI width and channel SNR. (a) B-Mode and MIST images across selected channel SNR values and MIST ROI widths. (b) MIST image statistics as a function of ROI width, with each line indicating a different channel SNR. (c) MIST image statistics as a function of channel SNR, with each line indicating a different ROI width. All MIST images and statistics use 1λ spatial averaging. Plots show the average value across 5 speckle and noise realizations (error bars are omitted for ease of visualization), and images are shown in 70 dB dynamic range.

Fig. 4:

Images of the lateral edge phantom. Conventional B-Mode is shown at the top, and MIST images (1λ kernel) using ROI widths of 0.5, 1.0, and 2.0 are shown at the bottom. The small ROI width demonstrates the best edge resolution, but with high rates of image dropouts and reduced speckle smoothness. Increasing ROI width eliminates image dropouts, but degrades edge resolution.

Fig. 5:

Measured statistics from the lateral and axial edge phantom simulations as a function of ROI width and axial kernel size. Increasing ROI width improves speckle SNR, reduces dropouts, and reduces lateral resolution. Axial resolution is unaffected by ROI width, but is degraded by using a larger axial kernel. Error bars represent the standard deviation across 10 speckle realizations.

Fig. 6:

Aggregate plots of lateral (left) and axial (right) resolution vs. speckle SNR as a function of MIST ROI width and axial kernel size. MIST lateral resolution is compared with that of spatial compounding, and MIST axial resolution is compared with that of frequency compounding. Ellipses represent the standard deviation of the measurement (horizontal axis: resolution, vertical axis: SNR) across 10 speckle realizations.

Fig. 7:

Images of hyper- and hypoechoic targets acquired from a tissue mimicking phantom. B-Mode images are compared to MIST images with increasing ROI width. Measured contrast is plotted at right, with error bars representing averages across 5 speckle realizations. All images are shown with 60 dB dynamic range.

Fig. 8:
Phantom MIST images as function of kernel size. The ROI width was 1.0 for all images. Increasing kernel size improves speckle texture, but at a loss of axial resolution and lesion conspicuity.

Fig. 9:

Images of anechoic targets from a tissue-mimicking phantom. MIST images (as a function of ROI width) are visually compared to spatial and frequency compounding images. Corresponding statistics are shown in Fig. 10, with the lesion ROI indicated by the white circle, and the background ROI by the disk between the dashed black circles.

Fig. 10:

Statistics from the phantom images shown in Fig. 9 are compared between MIST, spatial compounding, and frequency compounding. All plots represent averages across 5 speckle realizations, with standard deviations indicated by the shaded regions. MIST error bars are removed for ease of visualization, but have comparable standard deviations to those of Fig. 2.

Fig. 11:

In vivo liver MIST images (as a function of ROI width) are visually compared to spatial and frequency compounding images. Corresponding statistics are shown in Fig. 12, with the lesion and background ROIs indicated in the lower-left image.

Fig. 12:

Statistics from the *in vivo* liver images shown in Fig. 11, compared between MIST, spatial compounding, and frequency compounding. Increased ROI width reduces MIST contrast, while increasing CNR, SNR, and gCNR. Spatial and frequency compounding CNR and gCNR reach a peak at moderate levels of compounding.