Beamforming of Ultrasound Signals from 1-D and 2-D Arrays under Challenging Imaging Conditions

by

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Dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Biomedical Engineering in the Graduate School of Duke University 2015
ABSTRACT

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Abstract

Beamforming of ultrasound signals in the presence of clutter, or partial aperture blockage by an acoustic obstacle can lead to reduced visibility of the structures of interest and diminished diagnostic value of the resulting image. We propose new beamforming methods to recover the quality of ultrasound images under such challenging conditions. Of special interest are the signals from large apertures, which are more susceptible to partial blockage, and from commercial matrix arrays that suffer from low sensitivity due to inherent design/hardware limitations. A coherence-based beamforming method designed for suppressing the in vivo clutter, namely Short-lag Spatial Coherence (SLSC) Imaging, is first implemented on a 1-D array to enhance visualization of liver vasculature in 17 human subjects. The SLSC images show statistically significant improvements in vessel contrast and contrast-to-noise ratio over the matched B-mode images. The concept of SLSC imaging is then extended to matrix arrays, and the first in vivo demonstration of volumetric SLSC imaging on a clinical ultrasound system is presented. The effective suppression of clutter via volumetric SLSC imaging indicates it could potentially compensate for the low sensitivity associated with most commercial matrix arrays. The rest of the dissertation assesses image degradation due to elements blocked by ribs in a transthoracic scan. A method to detect the blocked elements is demonstrated using simulated, ex vivo, and in vivo data from the fully-sampled 2-D apertures. The results show that turning off the blocked elements both reduces the near-field clutter and improves visibility of anechoic/hypoechoic targets. Most importantly, the ex vivo data from large synthetic aper-
tures indicates that the adaptive weighing of the non-blocked elements can recover the loss of focus quality due to periodic rib structure, allowing large apertures to realize their full resolution potential in transthoracic ultrasound.
To friends and family for always believing in me.
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1

Background and Introduction

1.1 Overview

Chapter 1 offers a brief introduction to medical ultrasound imaging and builds clinical motivation for the development of methods that will improve ultrasound image quality. The fundamentals of ultrasound image formation and associated limitations/challenges are presented first. Particular sources of image degradation such as phase aberration, clutter, and blocked elements are discussed together with some of the existing imaging methods to alleviate for them. The last section gives an overview of 2-D arrays as one of the important tools to improve image quality and diagnostic value of ultrasound.

Chapters 2 through 5 contribute novel methods for beamforming ultrasound signals under challenging conditions. In particular, Chapters 2 and 3 discuss suppression of *in vivo* clutter via Short-lag Spatial Coherence (SLSC) Imaging, as implemented on a 1-D and a 2-D array, respectively. Chapter 2 was published in *Ultrasound in Medicine and Biology* under title ”In Vivo Application of Short-Lag Spatial Coherence Imaging in Human Liver” [59]. Work in Chapter 3 was published in *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control* under ”Short-lag Spatial Coherence Imaging on Matrix
Arrays Part II: Phantom and In Vivo Experiments” [58]. While both chapters discuss the in vivo results in liver, the beamforming principles presented therein also apply to imaging other tissues where suppression of clutter is necessary.

A specific problem of imaging in the presence of blocked array elements is addressed in Chapters 4 and 5. Chapter 4 covers detection of blocked elements and their impact on visualizing anechoic/hypoechoic targets in simulation and in vivo. In Chapter 5, blocked element detection and compensation schemes are applied on large coherent 2-D apertures. In particular, reverberation clutter and point-spread functions are measured ex vivo to assess improvements in image quality when the blocked elements are turned off and the intercostal subapertures are coherently summed, compounded, or adaptively weighted to recover k-space response of a fully sampled array. Chapters 4 and 5 are written in a journal-paper format but have not been submitted for publication yet.

1.2 Clinical Motivation

Ultrasound imaging is widely used in clinical practice to provide real-time and non-invasive visualization of anatomy and pathology. Due to low cost and high specificity of the modality, periodic ultrasound exams are recommended as a part of standard surveillance procedure for a range of liver diseases including non-alcoholic fatty liver disease and hepatocellular carcinoma [8, 18, 63, 64, 88, 103]. Ultrasound imaging is also an integral part of emergency and intensive care units where real-time feedback is critical for well-being of a patient. In that regard, many studies list bedside echocardiography and Doppler ultrasound as irreplaceable tools for emergency diagnosis of cardiac pathologies [2, 108, 109], and for monitoring cardiac function during surgery [46, 83]. According to Lichtenstein et al. [73], a routine ultrasound exam in an intensive care setting may change therapeutic plans for up to 25% of admitted patients. Lack of ionizing radiation combined with its real-time nature makes diagnostic ultrasound the imaging modality of choice when
it comes to monitoring fetal health.

The quality of clinical ultrasound images (and their diagnostic value) can be compromised by tissue inhomogeneities and poor acoustic windows [37, 50, 51, 89, 94, 104, 110]. Tissue inhomogeneities imply deviations of speed of sound from the expected value, which causes aberrations of the acoustic wavefront (so-called phase aberrations). Phase aberrations result in a broader ultrasound beam and increased side-lobe levels making it more difficult to resolve tissue boundaries and small structures\(^1\) [89, 106, 110]. Phase aberrations have been measured in breast [37, 110], liver [89, 94], and transcranial ultrasound imaging [95]. In addition to phase aberration, tissue inhomogeneities can cause waves to undergo multiple scattering events (reverberation) before impinging on the transducer surface. Reverberant echoes add noise and can overwrite signals originating at larger depths in an ultrasound image.

A poor acoustic window, defined as the presence of a strongly attenuating, distorting, or reflecting structure along the imaging path, is another major challenge in diagnostic ultrasound with reported incidence of over 60% in the low quality abdominal scans [104]. Ribs, scar tissue, poor abdominal muscle tone, abdominal gas, and shallow breathing have been listed as some of the common difficulties to obtaining a good acoustic window in abdominal imaging. Transthoracic ultrasound is also troubled by limited acoustic windows as the air and rib cage prevent significant penetration of ultrasound waves [49]. In a clinical study of 183 patients, the sensitivity and specificity of transthoracic ultrasound in detecting mediastinal masses\(^2\) were evaluated using CT as the 'gold standard' [121]. Due to limited acoustic window, the posterior mediastinum and paravertebral regions were poorly visualized with a sensitivity of 11% or less.

In the following, we focus on two particular subsets of challenges in ultrasound im-

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\(^1\) Degradation of ultrasound beam due to phase aberration is more thoroughly discussed in Section 1.4.

\(^2\) Mediastinal tumors form in the area of the chest that separates the lungs. This area is surrounded by the breastbone in front, the spine in back, and the lungs on each side.
age formation. First, reverberation due to tissue inhomogeneities within the subcutaneous fat layer can cause acoustic noise known as clutter that degrades visibility of anechoic/hypoechoic targets. Second, when parts of the aperture are blocked by ribs during a transthoracic scan, image quality is degraded by a combination of limited acoustic window and tissue inhomogeneities. The clinical impact of clutter and blocked elements are discussed in sections 1.2.2 and 1.2.1, respectively.

1.2.1 Problem of Image Clutter

Clutter is a type of acoustic noise that appears as an overlaying haze in images and obscures visibility of in vivo structures [68, 99]. In cardiac applications, clutter can impede detection of thrombi, tumors, and other abnormalities. Between 10 and 20% of routine echocardiograms are reported as suboptimal due to clutter [86]. Shmulewitz et al. showed in a study of 140 patients that there is also a strong association between clutter and poor image quality in abdominal sonography, with clutter reported in about 60% of low-quality abdominal scans [104].

Image degradation due to clutter has become more clinically relevant with the rise of obese population in the United States. According to National Health and Nutrition Examination Survey from 2008, 68% of adult population in the U.S. is overweight or obese [36]. While obesity in itself is not necessarily a cause clutter [104], many factors that contribute to clutter, including thick layers of subcutaneous fat and fat/connective tissue interfaces, loose abdominal musculature, and large body habitus, are typically present in obese and overweight individuals and can lead to poor image quality. Indeed, for these groups of patients, low sensitivity values (of ultrasound) have been reported in diagnosing fatty liver disease and hepatocellular carcinoma [18, 90]. In echocardiography, the occurrence of suboptimal exams is recorded to be three times higher in obese patient population than that in normal-weight patients [33]. To improve quality of cardiac scans in obese patients, use of contrast agents is frequently required and the exam-times are longer (than
for normal-weight patients) increasing the exam cost. Further, in a study involving over seven thousand gravid women, Hendler et al. showed that maternal obesity significantly limits visualization of the fetal heart [48]. Despite the use of state-of-the-art ultrasound scanners in the study, the fraction of obese patients that had suboptimal ultrasound exams remained at over 35%. To improve this statistic, advanced signal-processing techniques are needed that will allow formation of high-quality ultrasound images in the presence of clutter.

1.2.2 Problem of Blocked Elements

In abdominal imaging (or therapy), transducer elements are often blocked by the ribs. This leads to two types of distortions discussed above; it introduces sound speed error and it limits the acoustic window. Ribs present an obstacle in sound wave propagation as a large portion of energy gets reflected from the ribs due to high mismatch in sound speed and density between soft tissue and bone. Waves that end up propagating through the ribs do so at different speeds (than the one accounted for in time-delay calculations) introducing significant phase aberrations. As a part of their transcostal high intensity focused ultrasound (HIFU) feasibility study, Aubry et al. measured these types of distortion in simulations and ex vivo experiments [3]. In both cases, they found that waves that propagated through bone had pressure amplitude about 6 times lower than waves that propagated through soft tissue (in between the ribs). Degraded beampatterns associated with trans-rib imaging had a 1.25 mm spreading in the mainlobe half-width and a 20 dB increase in the sidelobe level.

Scar tissue leads to degradation of image quality via similar mechanisms as the ribs do; dense layers of connective tissue present in a scar cause strong reflection and distortion of ultrasonic wavefronts. While suboptimal liver scans due to abdominal scars are often encountered in the clinic, to our knowledge, there has not been a thorough study dedicated to this subject.
Inoperable transducer elements are another (related) cause of distortion of the ultrasound beam. Weigan et al. showed in a clinical study that two or more consecutive elements that suffer from a loss in transmit/receive sensitivity (so-called dead elements) can have a significant negative impact on the overall image quality [120]. Elements can experience a reduction or loss in sensitivity due to transducer delamination (detachment of backing material, the matching layer, or the lens from one or more elements), a break in the transducers cable, a short circuit, or damaged piezoelectric material, all of which can result from the constant use of transducers in the clinic. A study conducted by Martensson et al. in 32 hospitals across Sweden reported 39% of the inspected transducers suffered one of the listed defects [85]. Delamination and cable breaks, which usually affect multiple elements, constituted 96% of the defective transducers. Despite introducing annual quality controls as a part of standard protocol for testing equipment in participant hospitals, the incidence of transducer defects remained high with 27% of tested transducers being defective in the follow up study [84].

Problems of blocked and inoperable elements are becoming increasingly important as manufacturers continue to develop larger arrays in an attempt to improve quality of in vivo images. 1.5-D and 2-D arrays with big footprints and high number of elements are more likely to experience a partial blockage that can offset the expected improvements in resolution and contrast. It remains critical to find the point of diminishing returns for the aperture size in the presence of acoustic obstacles, and to develop beamforming methods that will allow for effective use of larger arrays in such environments.

1.3 Conventional Ultrasound Imaging

Clinical ultrasound imaging is usually performed with an array of elements that are designed to both transmit and receive acoustic pulses. Transmit pulses on the individual elements are electronically delayed to create a focused ultrasound beam and insonify
the tissue region of interest. Backscattered echoes are then recorded (using the same ele-
ments), delayed, and summed to focus the energy coming from a desired location. This
method of creating a receive ultrasound beam is known as delay-and-sum (DAS) beam-
forming. For a single transmit event, a different set of receive delays is usually applied
to focus the element data at each axial locations (or for a range of locations), the process
called dynamic receive focusing.

Transmit pulses used in ultrasound imaging are typically in the radio frequency (RF)
range. After delaying and summing the signals from the individual elements, the result-
ing RF line is envelope detected, meaning the carrier frequency is removed and only the
amplitude information is saved, yielding an A-line. To obtain a full B-mode image, the
transmit beam is swept laterally across the field of view and an A-line is created for every
transmit event. Envelope detected data is log compressed for display purposes.

1.3.1 Delay and Sum Beamforming

Delaying pulses on transmit and receive has an effect similar to that of an optical lens
used to focus light; it improves system’s sensitivity to waves coming from the desired
location. Time delays required to focus the transmit (or receive) beam at the point $P(r, \theta)$
can be calculated using simple geometric relationships according to the formula below

$$\Delta t_n = \frac{-x_n^2}{2rc} - \frac{x_n \sin \theta}{c}. \tag{1.1}$$

In equation 1.1, $r$ and $\theta$ are the polar coordinates of point $P$ with respect to the center
of the transducer, and $x_n$ is the lateral position of the $n^{th}$ transducer element. It is also
assumed that the wave propagates through the medium with the uniform speed $c$ (typically
$c = 1540 \, m/s$) and that $r >> x_n$.

Time delays align pulses from the individual elements to effectively create plane-waves
at the focus. The pressure distribution of the transmit or receive beam at the focal depth,
Figure 1.1: A simulated lateral PSF of an ultrasound system that uses a 15 mm, 75-element, linear array. Fractional bandwidth of the array is 0.5 and the pulses are transmitted at 4 MHz center frequency. The width of the mainlobe (at half maximum) is approximately 0.8 mm as predicted by the Fourier transform relationship ($\lambda z_0 / D$). The highest sidelobe levels are about -27 dB.

Figure 1.2: A Gaussian-weighted sinusoid transmitted by the system with the lateral response in Figure 1.1. The waveform was created by exciting the transducer with a 5-cycle sinusoidal pulse with center frequency of 4 MHz.

Often called a beampattern, can then be approximated by taking a Fourier transform of the aperture function [43]. For a rectangular aperture and assuming a single frequency wave, the beampattern is a $\text{sinc}$ function with the mainlobe width (at half maximum) of $\lambda z_0 / D$ and side-lobe levels of -13.26 dB. Here, $\lambda$ is the wavelength of the transmitted (or received) wave, $D$ is the size of the aperture, and $z_0$ is the focal depth. The mainlobe width is often used to define system resolution which is the ability of the system to distinguish between the two closely spaced signals. The Fourier transform relationship indicates that higher resolution is obtained by using larger apertures and higher transmit frequencies. The side-lobe levels in the beampattern determine contrast, i.e. the system’s ability to distinguish the signal of interest from the background signal. If the transmit and receive beams are focused at the same location, the pulse-echo sensitivity of the system equals the product of the individual beampatterns due to transmit and receive focusing. For the same size rectangular aperture used on both transmit and receive, it is simply a $\text{sinc}^2$ function.

---

3 Specifically, a beampattern describes sensitivity of an imaging system to incoming waves as a function of their direction.
For a system employing DAS beamforming, pulse-echo sensitivity of the system can also be directly measured by creating an image of a point target. The system response to a point target, also known as the point spread function (PSF), is a two-dimensional function that can be factored into separate lateral and axial responses at the focus. For DAS beamforming, the lateral PSF is the same as beampattern. The simulated lateral PSF of an ultrasound system employing a 15 mm, 75-element, linear array that has 0.5 fractional bandwidth and transmits at 4 MHz center-frequency is shown in Figure 1.1.

The PSF in the axial dimension is primarily determined by the shape of the transmit pulse. For a Gaussian weighted sinusoid, the axial resolution at the focus is approximated by $n\lambda/2$ where $n$ is the number of transmitted cycles. A Gaussian weighted sinusoidal pulse transmitted from the system with the lateral response plotted in Figure 1.1 is shown in Figure 1.2.

1.3.2 Speckle Statistics

Assessing performance of an ultrasound system only in terms of its ability to detect a point target has a limited applicability to in vivo imaging as there are few real point targets in the human body. A more common scenario in imaging human tissue is to insonify lots of sub-wavelength scatterers that cannot be resolved individually and whose amplitudes and positions vary according to some probability distribution. Depending on their relative phases for a particular realization, echoes from these scatterers add together at the face of the transducer constructively or destructively, resulting in a pattern of dark and bright regions called speckle, in the final ultrasound image. To characterize ultrasound images (and system performance) in the presence of speckle, the use of 1st and 2nd order image statistics is required.

Speckle patterns due to laser illumination have been extensively studied in optics [42] and the results for the 1st and 2nd order speckle statistics have been extended to ultrasound by several authors [13, 34, 116]. Wagner et al. [116] report speckle statistics for the
case of large number of randomly dispersed small scatterers (more than 10 scatterers per resolution cell), assuming phases of the scatterers are uniformly distributed between 0 and $2\pi$, and assuming the phase and amplitude of a single scatterer are independent of those of other scatterers and of each other. In that case, the envelope-detected signal $V$ can be described by a Rayleigh probability distribution:

$$p(V) = \frac{V}{\sigma^2} \exp \left( -\frac{V^2}{2\sigma^2} \right).$$

(1.2)

In equation 1.2, $\sigma^2$ is the variance of the complex signal recorded on the aperture and it depends on the mean-square scattering amplitude of the particles in the imaged tissue. The mean and the variance of $V$ are given by:

$$\langle V \rangle = \left( \frac{\pi}{2} \right)^{1/2} \sigma,$$

(1.3a)

$$\text{Var}(V) = \left( \frac{4 - \pi}{2} \right) \sigma^2,$$

(1.3b)

where the angled brackets are used to designate the expectation operator. The quantity $\langle V \rangle / (\text{Var}(V))^{1/2}$ is called the speckle SNR and (under the previously stated assumptions) is found to be a constant, $1.91$. Thus, the speckle SNR is independent of scattering properties of imaged tissue or imaging system being used.

In addition to knowing the properties of signal at a single location in the speckle pattern, it is important to know how these properties change over space. The autocorrelation and the autocovariance of speckle are (interchangeably) used to convey the average similarity between the signals measured at two locations in the speckle pattern, as a function of their separation in space\(^4\). For the case of diffuse scatterers discussed above, Wagner et al. [116] show that the autocovariance of complex amplitude (of ultrasound signal) can be expressed in terms of the PSF of the system, $g(x)$, as follows:

$$C_c(\Delta x) = a_0^2 g(-\Delta x) \otimes g^*(\Delta x),$$

(1.4)

\(^4\) The autocorrelation and the autocovariance are the same when both signals have zero mean.
where $a_0$ is the average scattering strength of the particles, $\Delta x$ is the distance between the locations $x_1$ and $x_2$ in the speckle pattern, and $\otimes$ is the convolution operator. When the function in (1.4) is normalized by its maximum value, it is called the normalized autocovariance in $c$ and is dependent only on the characteristics of the imaging system [116].

At the focus, the PSF, and therefore the autocovariance can be separated into factors arising from lateral and axial directions:

$$C_{c,x,z}(\Delta x, \Delta z) = C_{c,x}(\Delta x) \cdot C_{c,z}(\Delta z). \quad (1.5)$$

In equation 1.5, $x$ and $z$ are used to denote lateral and axial dimensions, respectively, and $C_{c,x}(\Delta x)$ and $C_{c,z}(\Delta z)$ are the corresponding covariances. For a rectangular aperture transmitting a Gaussian weighted sinusoid, the lateral and axial autocovariance functions of complex amplitude are given by:

$$C_{c,x}(\Delta x) = K_x \text{sinc}^2(\pi \Delta x D / \lambda z_0) \otimes \text{sinc}^2(\pi \Delta x D / \lambda z_0), \quad (1.6a)$$

$$C_{c,z}(\Delta z) = K_z \exp(-\Delta z^2 / 4\sigma_z^2), \quad (1.6b)$$

where $D$ is the size of the aperture, $\lambda$ is the wavelength of the sinusoid, $z_0$ is the focal depth, $\sigma_z$ determines the width of the Gaussian envelope, and $K_x$ and $K_z$ are normalization constants.

In practice, the autocovariance functions of signal magnitude and intensity ($C_V(\Delta x)$ and $C_I(\Delta x)$, respectively) are used rather than the autocovariance in complex amplitude as the former two can be measured from a B-mode image. $C_V(\Delta x)$ and $C_I(\Delta x)$ are shown to be very similar (no more than 3% difference), and can be computed from $C_c(\Delta x)$ using formulas presented in [87] and [116]. Measured normalized autocovariance functions for lateral and axial directions are shown in Figures 1.3 and 1.4, respectively. Figures are recreated from [106] and [115] and the original measurements were made on tissue mimicking phantoms. Distance is normalized in both plots to better convey the general shape of the functions.
Figure 1.3: A measured lateral autocovariance function of the speckle pattern. The plot is recreated from [106] and the original measurements were made on a tissue mimicking phantom. Distance is expressed in units of $\lambda z/D$ to better convey the general shape of the function. Notice that FWHM, location of the first zero, and the area under the curve are all close to the lateral dimension of the PSF.

Figure 1.4: A measured axial autocovariance function of the speckle pattern. The plot is recreated from [115] and the original measurements were made on a tissue mimicking phantom. Distance is expressed in units of $\sigma$ to better convey the general shape of the function. FWHM, location of the first zero, and the area under the curve are all close to the axial dimension of the PSF.

The width of the autocovariance functions can be used to determine the minimum spacing between the independent samples in a B-mode image. The width is typically measured at half-maximum, or as the location of the first zero. Correlation cell size, $S_c$, is another related metric developed to assess the sampling rate in a B-mode image. It is defined as the area under the normalized autocovariance function in intensity (or magnitude)

$$
S_c = \int_{-\infty}^{+\infty} d(\Delta x)C_x(\Delta x)/C_x(0).
$$

(1.7)

Wagner et al. showed that the correlation cell size is similar to the dimensions of the PSF [116]; for the lateral dimension, $S_c = 0.87\lambda z_0/D$, and for the axial dimension $S_c = 2.51\sigma_z$ with $\lambda$, $D$, and $\sigma_z$ denoting the same quantities as in (1.6). For these reasons, speckle size is often used as an alternative resolution metric.\(^5\) In Figures 1.3 and 1.4, for both lateral and axial autocovariance functions, FWHM, the location of the first zero, and the area

\(^5\) Conceptually, the correlation cell size is indicative of the amount of information that can be obtained for a given imaging configuration in a single B-mode scan. This property of the imaging system can be also characterized by the PSF.
under the curve are all similar to the corresponding dimension of the PSF.

1.3.3 Covariance of the Received Pressure Field

When diffuse scatterers in tissue are coupled with a transmit beam, they act as an incoherent source\(^6\). Statistical properties of the wavefields emanating from incoherent sources have been extensively studied in optics and a thorough review can be found in [42]. In particular, the spatial coherence of a wavefield describes the average similarity between two of its points as a function of their separation, and can be used to characterize signals received across the aperture.

The Van Cittert-Zernike (VCZ) theorem predicts the coherence of the wavefield propagating away from an incoherent source as the Fourier transform of that source’s intensity distribution. Mallart and Fink applied the VCZ theorem to pulse-echo ultrasound [81], and derived the expression for normalized covariance of the received pressure field when imaging diffuse scatterers:

\[
C'_{rf}(\Delta x) = \frac{1}{C_{rf}(0)} \int_{-\infty}^{+\infty} |H(\varepsilon)|^2 \exp \left[ -j \frac{2\pi}{zc} (\Delta x \varepsilon) \right] d\varepsilon. \tag{1.8}
\]

In equation 1.8, the normalized covariance \(C'_{rf}(\Delta x)\) is a function of distance between the observation points \(x_1\) and \(x_2\), and \(H\) is the transmit beam amplitude. Normalized spatial covariance is independent of focal length and transmit frequency and can be used to infer shape of the transmit beam [82]. Utilizing properties of the Fourier transform, the covariance can also be expressed in terms of the autocorrelation function of the transmit aperture. When using a rectangular aperture of size \(D\) to insonify a region of diffuse scatterers, the normalized covariance of received presure field is a triangle function with base \(2D\). It is worth noting that these results are valid only when the observation points \(x_1\) and \(x_2\) are located on the focused surface [81].

\(^6\) Incoherent source is a source that has statistical properties of white noise, i.e. its power spectrum is a constant.
1.4 Beamforming Limitations and Image Degradation

Theory presented in Section 1.3 has been developed to characterize an ultrasound system assuming ideal imaging conditions. In the following, we expand this theory to include more realistic imaging scenarios. Changes of the beampattern, speckle statistics, and (spatial) correlation of backscattered pressure fields are discussed to account for the presence of phase aberration, reverberation, and limited acoustic window. Understanding of those mechanisms is used to predict image degradation caused by the blocked elements.

1.4.1 Effects of Phase Aberration

The time-delay calculations in equation 1.1 assume that waves propagate through the tissue with a uniform speed $c$. In the presence of sound-speed inhomogeneities, however, different parts of wavefront will propagate at different speeds so the delayed pulses from the individual elements will add out of phase at the focus. The beampattern in the presence of phase aberration has been characterized through simulations [106, 110] and through in vitro and in vivo experiments [89]. The results indicate widening and decrease in amplitude of the mainlobe, and increased energy level in the tails of the function. A lateral shift of the mainlobe (steering error) is also possible if the phase aberrator has a periodic structure to it [106]. Following the definitions of lateral resolution and contrast outlined in section 1.3.1, these changes of the beampattern imply reduced lateral resolution and lower contrast of the B-mode images in the presence of phase aberration.

Degradation of beampattern due to phase aberration also affects the 1st and 2nd order speckle statistics. Trahey et al. showed through simulations and phantom experiments that the average brightness of the speckle decreases with broadening of the ultrasound beam (caused by phase aberration) [112]. As the energy of the beam shifts from mainlobe to tails of the function, a larger number of diffuse scatterers is insonified at lower amplitude. The mean value of speckle brightness $\langle V \rangle$ depends on the mean-square scattering amplitude of
the insonified particles as indicated by equation 1.3. Hence, if more particles are insonified at lower energy, the sum of squares of their amplitudes will be smaller and the average speckle brightness will be lower. Similar trend can be expected of the speckle pattern free of phase aberration but away from the transmit focus where delayed pulses add out of phase and ultrasound beam becomes broader.

In a companion paper to [112], Smith et al. explored the effects of phase aberration on the speckle size [106]. In the axial dimension, phase aberration has the effect to lengthen the overall pulse, which extends the axial speckle accordingly. In the lateral dimension, speckle breaks up into smaller, correlated patches as the normalized autocovariance function adopts a periodic behavior. Similar trend can be expected of the speckle pattern free of phase aberration but away from the transmit focus where delayed pulses add out of phase and ultrasound beam becomes broader.

7 Side-lobes of the lateral autocovariance function indicate that the speckle cell size (as defined in equation 1.7) should be used to infer sampling rate of an ultrasound system in the presence of phase aberration, rather than the FWHM of the autocovariance function. Indeed, while the FWHM (of the autocovariance function) decreases in the presence of phase aberration, the speckle cell size increases (by up to 50%) reflecting a loss in the system’s sampling rate. It is important to note that the theoretical model used by Smith et al. assumes that at the focus, changes in the overall pulse length are small compared to changes in the beampattern allowing for separate treatment of the autocovariance functions in lateral and axial dimensions.

The statistical properties of backscattered fields are also affected by sound-speed inhomogeneities. Utilizing basic properties of Fourier transform and the VCZ theorem, Mallart and Fink estimated the general shape of the normalized covariance function of the received pressure field generated by the diffuse scatterers in the presence of phase aberrations [81, 82]. As the transmit beam becomes wider in the presence of an aberrator, the VCZ theorem predicts the spatial covariance function to become narrower. A more systematic approach

7 Normalized autocovariance of lateral speckle can be predicted from equation 1.6. If the aberration-free, pulse-echo response \( \text{sinc}^2 \) is replaced with aberrated beam intensity profile, use of the convolution operator in (1.6) leads to narrower mainlobe and the presence of side-lobes in the theoretical autocovariance function. Smith et al. confirmed these predictions by measuring the autocovariance function in a set of phantom experiments where they introduced random delays to channel data to mimic phase aberration [106].
was provided by Walker and Trahey [117] who modeled the aberrator as a near-field phase screen and derived the following expression for the normalized covariance of the pressure field received from a speckle generating target

\[
C_{rf}^t(f_z) = \frac{\int_{-\infty}^{+\infty} T(X_a)T^*(X_a-\Delta X)dX_a}{\int_{-\infty}^{+\infty} T(X_a)T^*(X_a)dX_a} \times \exp \left( \left( -2\pi f_z \right)^2 (R_{\tau\tau}(0) - R_{\tau\tau}(\Delta X)) \right).
\] (1.9)

In equation 1.9, \( C_{rf}^t \) is a function of transmit frequency \( f_z \), \( T(X) \) is the transmit aperture function, and \( R_{\tau\tau} \) is the spatial autocovariance of the aberrator. This model showed excellent agreement with the simulation results predicting a sharp drop in the spatial covariance function in the presence of a severe aberrator [117].

1.4.2 Reverberation Clutter

Tissue inhomogeneities can also lead to reverberation (multipathing), which is another significant source of image degradation [14, 67, 99]. Layered tissue structures or diffuse inhomogeneities can cause waves to undergo many scattering events before impinging on the transducer surface. If waves resonate between the parallel tissue interfaces (such as those found in a vessel wall), received echoes will write bright periodic bands over the signal of interest. If waves insonify a region with diffuse inhomogeneities, or if there is a large number of non-parallel interfaces (e.g. fat-connective tissue interfaces in obese individuals), receive channels will be corrupted with a less-coherent noise causing a sharp decorrelation of signal across the aperture [66]. This type of noise appears in images as diffuse haze and is called clutter.

While many methods for clutter reduction have been proposed recently, few analytic-form models of clutter appear in the ultrasound literature. In [24], Dahl et al. modeled clutter as additive white-noise, filtered with the transducer impulse response. In particular, they used FIELD II simulations to assess performance of short-lag spatial coherence (SLSC) imaging in lesion detection in the presence of clutter; the applied clutter model
yielded contrast and CNR trends that were in good agreement with the in vivo results [59]. Byram et al. modeled echoes from multipathing as linear-frequency-modulated sinusoids (i.e. chirps) in the aperture domain, and subsequently removed them from the overall signal to successfully reduce clutter in simulated and in vivo images [14, 15]. Pinton et al. [99] estimated image degradation due to clutter by numerically simulating wave propagation through a layer of abdomen. Simulations were based on the full-wave equation, which accounts for the effects of non-linearity, attenuation, and reverberation. By controlling the density and speed-of-sound maps, the effects of reverberation and phase aberration could be studied independently. Removing the sources of reverberation clutter recovered CNR of the anechoic lesion located at 3.5 cm depth by as much as 30% (of the control value obtained from the homogenous simulation); CNR of the anechoic lesion at 5 cm depth was increased by 16% of its control value.

1.4.3 Limited Acoustic Window

Beam degradation due to a limited acoustic window can be predicted by using a Fourier transform relationship between the pressure distributions at the face of the transducer and at the focus, as outlined in section 1.3.1. In particular, if an acoustic obstacle effectively prevents parts of the array from transmitting and/or receiving acoustic pulses, the degraded beampattern can be estimated by taking a Fourier transform of the newly-formed sparse-aperture function. A corrupt beampattern typically has higher side-lobe levels than the beampattern due to fully functional array. Additionally, if end-elements of the array are blocked, the overall aperture size is reduced and a wider mainlobe results [70].

Ramsdale and Howerton addressed a similar problem of beampattern degradation due to element failure in sonar arrays [101]. They found that the peak sidelobe level of the average beampattern is proportional to the ratio of the sum of the weights of the inoperative
elements to the sum of the weights of the operative elements

$$SSL_{\langle p(\theta) \rangle_{\text{max}}} \propto \frac{\sum a_n(\text{inoperative})}{\sum a_n(\text{operative})}. \tag{1.10}$$

Using equation 1.10, Ramsdale and Howerton found that a single faulty element leads to an increase in the maximum sidelobe level that corresponds to a $30^\circ$ maximum phase error across the array (approximately 3.5 dB). As the number of faulty elements increases, maximum sidelobe level increases and the shape of the sidelobes starts to depend more on the beampattern of the inoperative part of the aperture [101].

1.4.4 Image Degradation due to Blocked Elements

As stated previously, the loss of image quality in the presence of blocked elements can be explained as a combination of two factors, sound-speed inhomogeneities and a limited acoustic window. Both factors lead to broadening of the ultrasound beam and increased side-lobe levels, which in turn, causes a loss of resolution and decreased visibility of anechoic/hypoechoic targets. Further, the $1^{\text{st}}$ and $2^{\text{nd}}$ order speckle statistics are expected to follow the changes in the beampattern outlined in Section 1.4.1. Speckle is expected to break up into smaller, correlated patches and its average brightness should be lower.\textsuperscript{8} Backscattered echoes should rapidly decorrelate across the receive aperture as the signals from the blocked elements experience attenuation, a random phase shift, and increased amount of reverberation noise due to acoustic-impedance mismatch between the soft tissue and bone. The nearest-neighbor cross-correlation between the blocked elements should be particularly low. Acoustic noise due to reverberation is expected to appear as clutter in the near-field region of the final B-mode image.

\textsuperscript{8} The normalized autocovariance function of lateral speckle is expected to exhibit a periodic behavior due to increased side-lobe levels in the beampattern. Therefore, speckle cell size (defined in (1.7)) should be used to assess the number of independent samples in a degraded B-mode image.
1.5 Adaptive Imaging Methods

The beampattern shown in section 1.3.1 assumes uniform weighting of the individual channel signals. To reduce the width of the mainlobe or to decrease the sidelobe levels different weighting (apodization) schemes can be applied to the channel data. When the weights are independent of the channel data (conventional beamforming), there is a trade-off between the mainlobe width and the sidelobe levels of the resulting beampattern. Some of the typically used (non-adaptive) apodization functions are Gaussian, Hamming, Dolph-Chebyshev, Hann, and Kaiser windows [60].

System sensitivity (in the lateral dimension) can be further improved if the channel weights are allowed to change with the received signals, process known as adaptive beamforming. Adaptive weights are usually chosen to minimize some cost function subject to a constraint. For example, in a Minimum Variance Distortionless Response (MVDR) beamformer, weights are chosen that minimize the total output power while keeping the response to signal coming from a desired direction unchanged [60]. In other words, the weight vector \( \mathbf{w}_{MVDR} \) is a solution to the following constrained optimization problem

\[
\min_{\mathbf{w}} (\mathbf{w}^T \mathbf{R} \mathbf{w}) \quad \text{subject to} \quad \mathbf{e}^T \mathbf{w} = 1,
\]

where \( \mathbf{R} \) is the cross-correlation matrix of the received channel data, \( \mathbf{e} \) is a so-called steering vector that specifies the direction of the desired signal, and \(^T\) stands for the conjugate transpose operator. Using the method of Lagrange multiplier \( \mathbf{w}_{MVDR} \) is calculated as

\[
\mathbf{w}_{MVDR} = \frac{\mathbf{R}^{-1} \mathbf{e}}{\mathbf{e}^T \mathbf{R}^{-1} \mathbf{e}}.
\]

(1.11)

Adaptive weights defined by (1.11) result in suppression of interference (signal coming from undesired direction) while preserving the signal of interest. MVDR is the most effective in suppressing isolated, point-like targets that are not in the immediate proximity

---

9 Applying weights to the individual channel data can be conceptualized as a spatial filtering operation. Therefore, windowing functions that are used to filter time-series data can be also used for aperture apodization.
of the desired signal. In the presence of distributed targets, the performance of MVDR approaches that of DAS beamforming.

The adaptive imaging methods can be also used to improve image quality in the presence of phase aberration, clutter, and blocked or missing elements. Some of the most commonly used such methods are reviewed in the remainder of this section.

1.5.1 Phase Aberration Correction

Several methods have been developed to improve a beampattern in the presence of phase aberration [23, 32, 35, 38, 76, 77, 91, 93, 123], and they can be grouped based on the model of the aberrator they employ. When the aberrator is modeled as a thin screen at the face of the transducer (the so-called near-field phase-screen model), the received waveforms are assumed to be time-delayed versions of their non-aberrated counterparts. If this assumption is true, the ideal beampattern can be recovered by estimating the tissue-induced time-delays and applying them to the individual channel signals so they can be summed in phase.

Liu et al. [77] applied the near-field phase-screen model to find a least-squares (LS) estimate of the arrival-time profiles for the wavefronts that propagated through the excised sections of human abdomen. Specifically, they measured the (tissue-induced) time-delays between the neighbouring channels from the peak of their cross-correlation functions. A large number of delay measurements (four nearest-neighbour delay values per channel) allowed them to model a highly over-determined system and compute an LS estimate of the arrival-time\(^{10}\) for each channel. The corrected beampatterns showed the -10 dB effective width that is on average 30% smaller than the effective width of the non-compensated beampattern, and is 4% larger than the effective width of the ideal (non-aberrated) beampattern. The average ratio of the energy outside of the -10 dB effective-width-region to the energy inside the region is 1.81 for the uncompensated, 0.93 for the compensated, and

\(^{10}\) The arrival time for a channel can be thought of as a time-delay relative to the reference waveform.
A similar LS-based phase-aberration correction technique was successfully applied in [23, 30, 40], but in combination with the property of phase enclosure, which states that the signal-phases (or time-delays) along any closed path on the aperture have to add to zero. If the system of equations is allowed to include the delay measurements at higher lags (in addition to neighbouring elements), phase enclosure can provide for multiple measurements for any pair of channels in the aperture which increases accuracy of the arrival-time estimates.

Under a more realistic imaging scenario, parts of the wavefront experience time-shifts at some distance away from the transducer surface. As the time-shifted wavefront continues to propagate, the amplitude and shape distortions develop and the received signals lose similarity (coherence) across the channels. In that case, estimating the delays from the channel data is more difficult, and delaying the individual channel signals alone is not sufficient to fully recover the beampattern. Indeed, in [76], Liu et al. showed that the phase-aberration correction can be improved if the phase-screen is modeled at some (axial) distance away from the transducer, and the received waveforms are back-propagated to the phase-screen location before estimating the time-delays. The axial location of the phase-screen was determined where the (back-propagated) signals showed the highest degree of similarity along the array dimension. For the beampatterns measured on 14 samples of human abdomen, the -10 dB peripheral energy ratio decreased on average from 0.63 for the time-shift compensation alone to 0.47 when the time-shift compensation was preceded by back-propagation.

For the time-delay focusing techniques to be effective, speed-of-sound inhomogeneities have to be confined to a thin region, i.e. they have to meet the assumptions of the phase-screen model. If the speed-of-sound inhomogeneities are distributed throughout the medium, the shape of the propagating wave gets distorted through refraction, diffraction, and multiscattering, and the adaptive channel-delays can no longer improve focusing. To achieve optimal focusing in the presence of such an aberrator, Fink et al. proposed the method of
time-reversal mirror (TRM) [32, 123]. Specifically, if a point-like source is placed at the (desired) target location, the aberrated wavefronts can be recorded on the aperture, time-reversed, and re-emitted. The energy at the target location is then maximized since the time-reversal of the aberrated waveform allows the inhomogenous transfer function between the array and the target to act as a matched filter. Corrected beampatterns measured in the phantom experiments in [123] demonstrate that the TRM can achieve high-quality focus for different positions and shapes of the aberrator. While the TRM is insensitive to the aberrator geometry/structure, it requires the presence of a point source at the focus making its in vivo application difficult.

1.5.2 Clutter Suppression via Coherence-based Imaging Methods

Low coherence of ultrasound signals across the receive aperture can be an indicator of low image quality. When a region of diffuse scatterers is insonified with a rectangular aperture of size $D$, the (spatial) covariance of receive pressure fields is expected to be a triangle function with base $2D$ (section 1.3.3). However, the spatial covariance decreases at a faster rate in the presence of phase aberration and reverberation (section 1.4). The idea behind most of coherence-based imaging methods is to identify and suppress the incoherent portions of the signal in order to reduce the effects of phase aberration and reverberation.

Some of the metrics based on the receive-signal coherence are listed below:

1) the Coherence Factor - defined as a ratio of the coherent sum to the incoherent sum of the received echoes, it was designed to measure the focus quality of an ultrasound imaging system and to measure the performance of phase-aberration correction algorithms [82],

2) the Waveform Similarity Factor - a metric similar to the Coherence Factor, it was introduced to measure similarity of the received waveforms along the array dimension, as they were back-propagated to determine the axial location of the phase screen and
to perform subsequent aberration correction [76],

3) the Generalized Coherence Factor - similar to the Coherence Factor and developed
to suppress phase-aberrated signals [71],

4) the Phase Coherence Factor and the Sign Coherence Factor - the two metrics were
based on the variance of phase of the received echoes across the aperture, and were
intended to reduce the off-axis scattering [16].

The latter three metrics were used to weight B-mode images on a pixel-by-pixel bases in
order to reduce the effects of phase aberration.

In an alternative approach, Walker and Trahey developed a translating aperture method
that uses multiple transmits to improve correlation of speckle across the receive channels
[117]. Specifically, if the aperture is translated between the transmits by the same amount
and in direction opposite to that of a desired receive-element lag, the decorrelation of
speckle due to (transmit-receive) geometry is eliminated, and only decorrelation due to
aberration remains. For the phase aberration correction schemes that rely on the near-
field phase-screen model, this technique can improve the estimates of tissue-induced time
delays resulting in a higher quality of corrected images.

Lediju et al. have recently developed a beamforming method called Short-Lag Spatial
Coherence (SLSC) imaging [66] that suppresses the incoherent portion of received echoes
and has the potential to reduce clutter. Unlike the previously described coherence-based
metrics that are used to weight B-mode images, SLSC imaging relies solely on the coher-
ence of back-scattered echoes, and not on their magnitude. Specifically, to determine the
value of a pixel in SLSC image, the spatial coherence curve is computed from the individ-
ual channel signals and integrated over the region of low lags. The exact implementation
of the SLSC method on 1-D and 2-D arrays is described in sections 2.2.1 and 3.2.1, re-
spectively. Simulated and in vivo SLSC images look comparable to conventional B-mode
images under noise-free conditions, and show dramatically improved visualization of ane-
choic and hypoechoic targets in a noisy environment [24, 25]. The beamforming principles
behind the SLSC imaging have been also applied to harmonic signals (the method called Harmonic Spatial Coherence Imaging or HSCI [25]), and towards power Doppler imaging for improved flow detection (Coherent Flow Power Doppler or CFPD [72]).

Other (non-coherence-based) approaches for clutter reduction include harmonic (DAS) imaging [5, 19], chirp-based signal decomposition [14, 15], and motion-based approach to clutter reduction [69].

1.5.3 Compensation for the Blocked and Missing Elements

To improve the beampattern in the presence of blocked or inoperable elements, the constrained optimization approach can be used to solve for the weights on the remaining elements. Er and Hui proposed to minimize the mean-square error in the mainlobe region\(^{11}\) while keeping the mean-square sidelobe levels within some user-defined boundary \(\varepsilon\) and forcing the weights of inoperable elements to zero [28]. As indicated by the simulated beampatterns, the resulting weight vector effectivelly reduces sidelobes for a small number of faulty elements. However, since the weights are not adaptive (despite being a solution to a constrained optimization problem)\(^{12}\), the DAS sensitivity pattern sets the upper limit on the method’s performance.

A common way to adaptively compensate the array beampattern in the presence of inoperable elements is to interpolate the signals on those elements. In that case, a constrained optimization problem can be formulated as

\[
\min_p (p^+ Q^+_{\text{min}} Q_{\text{min}} p) \quad \text{subject to} \quad \|L^+ p - x_{\text{operable}}\|_2^2 < \varepsilon ,
\]

with the solution given by

\[
p = (Q_{\text{min}} Q^+_{\text{min}} + \mu LL^+)^{-1} \mu L x_{\text{operable}} .
\]

\(^{11}\) Here, the error is defined as a difference between the actual array response and a desired array response.

\(^{12}\) The weights do not depend on the received signals and the locations of the inoperable elements are known \textit{a priori}. 

24
In other words, a full array data-set \( \mathbf{p} \) is reconstructed such that its noise component is minimized while keeping the distortion of the signals from the operable elements \( \mathbf{x}_{\text{operable}} \) within some value \( \varepsilon \). In equation 1.12, columns of \( \mathbf{Q}_{\text{min}} \) are eigenvectors that define the noise-subspace of the channel cross-correlation matrix \( \mathbf{R} \). \( \mathbf{L} \) is a selection matrix that specifies the positions of the operable elements, and the scalar parameter \( \mu \) controls the amount of noise suppression. Kazanci and Krolik modified this approach by solving the optimization problem in the beam-space rather than in the element-space and called it Beam-space Adaptive Channel Compensation (BACC) [61]. Assuming that the highest receive-beam sidelobes occur within the mainlobe of the transmit-beam and that the number of receive beams needs not be large, transforming from element-space to beam-space significantly improves computational efficacy of the algorithm. Simulation results show that BACC is capable of suppressing sidelobes and improving target detectability in the presence of distributed targets (clutter) or directional interference.

As discussed previously (section 1.4.3), the effects of blocked elements on the beam-pattern are similar to those caused by inoperable elements. Nevertheless, instead of trying to correct the distorted beampattern, Li et al. developed a method that compensates for the blocked elements by directly suppressing the contributions from the off-axis scatterers [70]. For every transmit beam, multiple receive beams are created (via DAS beamforming) to measure the source profile. Measured source profile can be represented by the convolution sum of the true source profile and the beampattern (degraded by the blocked elements)

\[
\mathbf{B} \mathbf{a} = \mathbf{x}
\]  

In equation 1.13, each column of matrix \( \mathbf{B} \) is a degraded beampattern centered around the direction of the \( i^{th} \) source \( \Delta_i \), vector \( \mathbf{a} \) contains the complex amplitudes of the scattering sources (targets), and vector \( \mathbf{x} \) is the measured complex source profile. The direction and amplitude of the most dominant targets can then be estimated as the solution to the
following minimization problem

$$
\hat{\Delta}_i, \hat{a} = \min \| \hat{B}\hat{a} - x \|_2.
$$

(1.14)

With $a$ and $\Delta_i$’s known, the undesired sidelobe contributions from the off-axis scatterers are easily removed from (the receive beam at) the transmit direction.

To construct the model in (1.13), Li et al. made the following assumptions:

1) the medium is insonified with a continuous wave so the degraded beampattern can be approximated by the Fourier transform of the sparse-aperture function where the blocked elements are weighted by zero and the active elements are weighted by one,

2) the number and position of blocked elements are known for each imaged point allowing matrix $B$ to be updated accordingly, and

3) the targets can be presented by delta functions.

In addition, the estimates of $a$ are obtained via the total least squares (TLS) method and as such, are robust to the imperfections in the model. The method was shown to be effective in improving phantom images of point-targets and distributed targets for a reasonable number of blocked elements. However, in the \textit{in vivo} setting, the targets would have to be classified before the method could be used since the TLS is not adequate for bimodal targets and anechoic regions.

1.6 Imaging with Matrix Arrays

The conventional ultrasound system described in section 1.3 uses a 1-D array of elements to scan a single plane in tissue. Electronic delays are applied to the individual elements to steer and focus ultrasound beam at the desired locations in the azimuth plane. In the elevation plane, a cylindrical ultrasound lens covering the aperture provides a fixed focus.

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13 Unlike the traditional least squares method which assumes that the model is correct and the error is confined to the observation vector, the method of total least squares allows for error to reside in both model and measurements. This improves robustness of the estimates but increases computational complexity of the algorithm.
This configuration imposes several limitations on image quality and potential applications. The small elevation dimension of the array (typically less than 2 cm), in combination with the fixed focus yields a relatively thick B-mode slice and significant contributions from the out-of-plane scatterers. Outside of the fixed focus, elevation resolution can be up to several times larger than lateral resolution, making the ultrasound beam highly asymmetric and limiting the detection rate of small targets. Simulation studies have compared the performance of 1-D and 2-D arrays when imaging small hypoechoic lesions, and reported a loss of target contrast for images created with the linear array [114]. Further, some adaptive imaging algorithms, such as most of the phase-aberration correction schemes and SLSC imaging show limited success when implemented on a 1-D array because the quantities they estimate (a phase-screen aberrator and the normalized spatial covariance, respectively) usually vary along both dimensions of the aperture [31, 54]. Completely averaging one of the dimensions degrades the accuracy of the estimate.

Arrays that have at least three rows of elements can also focus an ultrasound beam in elevation plane, with varying degrees of freedom. Following the nomenclature in [122], a 1.5-D array can apply dynamic focusing in the elevation dimension, but only along the center-axis of the transducer. 1.5-D arrays typically have three to five rows of elements, and have demonstrated reduced slice thickness and a more uniform beam profile in the elevation direction compared to linear arrays [22, 122]. In addition to variable depth focusing, a 1.75-D array can slightly deflect a beam in the elevation plane. Some 1.75-D arrays can steer up to 30 degrees in elevation while maintaining a reasonable beamwidth [47]. Although 1.75-D arrays contain a limited number of element rows (usually no more than 10), they proved successful in measuring and correcting for 2-D phase aberration profiles [23, 30, 31, 39]. In simulation and in phantom experiments, Fernandez et al. [31] showed that as the aperture sampling along the elevation dimension increases, the accuracy of a 2-D aberration profile improves, with as few as three rows of elements bringing significant improvements in accuracy over a linear array. Hyun et al. showed similar trends relating
aperture sampling (in either dimensions) and the quality of SLSC images [54].

2-D arrays can achieve full electronic steering, focusing, and aperture selection in the elevation dimension allowing them to scan complete 3-D volumes at high speeds [100, 105, 107]. To this end, they usually have a similar number of elements in both dimensions. One of the first 2-D arrays was a 17-by-17 phased array developed as a part of a real-time volumetric system at Duke University [100, 105]. Due to a limited number of system channels (32 on transmit and 32 on receive), active elements had to be sparsed through the aperture. Different array geometries, such as Mills cross, circular aperture, and combination of the two were tested on transmit and receive to optimize the 2-D pulsed-echo response.

Since then, 2-D arrays have been developed to have thousands of elements and the sparse sampling methods have been used widely to pass the aperture data to a limited number of system channels [4, 12, 27, 53, 74, 78, 119, 124]. Typically, the active elements are distributed so to minimize the mainlobe width while keeping the grating lobes under a reasonable level. Lockwood et al. [78] achieved this by choosing transmit and receive apertures that are analogous to the stationary and sliding parts of the Vernier scale (so-called Vernier arrays). The ‘sliding’ aperture has less elements and a slightly smaller element spacing than the ’stationary’ aperture, so that the resultant effective aperture approximates that of a fully populated array. In another approach, Davidsen et al. [27] explored performance of randomly populated sparse arrays; a random array with Gaussian distribution on transmit and uniform distribution on receive showed improved resolution and depth-of-field compared to standard Mills cross design and a random array with uniform distribution on both transmit and receive. A comprehensive overview of sparse periodic designs based on different combinations of symmetry is presented in [4], including symmetric and asymmetric periodicity, and periodicity along x-axis and y-axis, along diagonals, and along radii.

To allow use of all elements in a 2-D aperture while accommodating for a limited
number of systems channels, most of modern commercial 2-D arrays employ subaperture beamforming in the transducer handle. ASICs in the handle perform delay-and-sum beamforming on small groups of elements and partially beamformed data is passed on to system channels for further processing; this reduces the number of signals the scanner would have to process from several thousand to typically less then two hundred. While subaperture electronics brings down cable weights and overall system cost, they cause a significant loss of sensitivity in 2-D arrays [79]. In addition, the resultant inability to access radio-frequency (RF) data for each element inhibits the realization of many techniques requiring custom transmit sequences or advanced aperture-domain signal processing, including phase aberration correction and adaptive beamforming.

Small element size, electronics in the transducer handle, and use of broad transmit beam are the main causes of reduced sensitivity when imaging with 2-D arrays. Specifically, elements of a matrix array are small and therefore have high impedance (or low capacitance) resulting in poor impedance match with front-end electronics; this causes both low transmit power and low receive sensitivity [41]. In addition, it requires ASICs for partial-beamforming to be as close to elements as possible to minimize parasitic capacitance [79]. Electronics in the handle therefore have to be small and can operate only in low voltage regime, which further limits sensitivity of the array. Electronics in the handle also couples energy from an active element to the surrounding elements resulting in undesirable cross-talk [113]. Finally, to scan full volumes at real-time rates, broad transmit beams are typically used causing a loss in transmit resolution.

Despite their design limitations, matrix arrays offer a unique opportunity to visualize structures in three dimensions, non-invasively, and in real-time. This hold tremendous potential for many clinical applications including volume estimation of heart chambers and tumor masses, volumetric angle-independent flow imaging, and 3-D motion tracking of heart walls and valves. Beamforming methods that would mitigate loss of sensitivity and reduce the rate of suboptimal 3-D exams would secure a wider use of matrix arrays in
clinical practice.
Short-Lag Spatial Coherence Imaging on 1-D Arrays: Results of a Pilot Study on Human Livers

2.1 Introduction

Ultrasound is commonly used for surveillance and diagnosis of liver diseases because of its high specificity (75-98%), relatively low cost, and lack of ionizing radiation [8, 18, 64, 88, 90, 103]. In many hospitals, asymptomatic patients with an incidental elevation of liver enzymes receive periodic abdominal ultrasound scans in an attempt to diagnose early onset of non-alcoholic fatty liver disease (NAFLD), the most common form of liver disease [63, 88]. Hepatorenal echo contrast, liver tissue brightness, and vascular blurring are indicators typically used to detect and stage NAFLD [88]. In a similar manner, the American Association for the Study of Liver Diseases has recommended periodic ultrasound exams as a part of standard surveillance procedure for hepatocellular carcinoma (HCC) [10].

For both NAFLD and HCC, the role of ultrasound in diagnosing and staging the disease is sometimes limited by inadequate image quality. Most of the patients that are at risk of or are already suffering from NAFLD are categorized as overweight or obese (based on
their body mass index) and may yield low quality images. A study done on morbidly obese patients reports the sensitivity of ultrasound in diagnosing hepatic steatosis (fatty liver disease) to be only 49.1% [90]. The growing population of overweight and obese patients is also under increased risk of developing HCC. The American Association for the Study of Liver Diseases acknowledges that these patients are often not good candidates for HCC surveillance [10], where the reported values for sensitivity are as low as 65% [18].

The body habitus of overweight and obese patients introduces a variety of challenges in ultrasonic imaging, one of which is an increased level of acoustical noise known as clutter.

Clutter is a significant reason for diminished quality of ultrasound images of the liver [68, 97]. It appears as an overlaying haze or fill-in that obscures in vivo structures such as lesions and blood vessels and leads to inadequate visualization of liver anatomy and function. The three main sources of clutter that have been identified are phase aberration, reverberation among tissue layers, and off-axis scattering [97]. Many of these sources of clutter are present in overweight and obese individuals due to thick layers of subcutaneous fat and fat/connective tissue interfaces. As a result, there is a growing clinical need for ultrasound imaging techniques that would reduce clutter or improve image quality and allow for more patients to be effectively surveyed for liver diseases such as NAFLD or HCC.

Harmonic imaging and various phase aberration correction methods are examples of techniques developed to reduce clutter. Harmonic imaging is based on nonlinear wave propagation, which generates frequency components at integer multiples of the transmitted frequency. This phenomenon is negligible close to the surface of the transducer, which results in a reduction of near-field reverberation clutter [5, 19]. However, harmonic imaging does not suppress clutter originating from phase aberration; in fact, it is more susceptible to phase aberration than fundamental B-mode due to the higher receive frequency [97]. Phase aberration correction methods can reduce side-lobe levels and the effects of off-axis scattering [32, 35, 76, 92]. However, their potential to improve quality of fundamental
B-mode images is limited because of overlaying reverberation clutter [97].

Adaptive imaging methods based on spatial coherence of the pressure field present an alternative approach to improving image quality. Walker and Trahey developed a translating aperture technique to improve speckle correlation and thus facilitate near-field phase aberration correction [117]. Mallart and Fink introduced the Coherence Factor, defined as a ratio of the coherent sum to the incoherent sum of the received echoes, in an attempt to quantify focusing characteristics of ultrasonic imaging systems [82]. The Generalized Coherence Factor [71] is a coherence measurement similar to the Coherence Factor and was developed primarily to suppress phase-aberrated signals. The Phase Coherence Factor and the Sign Coherence Factor are based on the variance of phase of the received echoes across the aperture and are intended to reduce the off-axis scattering [16]. The Generalized Coherence Factor, Phase Coherence Factor, and Sign Coherence Factor are all used to weight the B-mode on a pixel-by-pixel basis in order to improve B-mode image quality.

We have recently developed a beamforming method called Short-Lag Spatial Coherence (SLSC) imaging [66] that suppresses the incoherent portion of the backscattered ultrasound field and has the potential to reduce clutter. We have also adapted SLSC imaging to the backscattered harmonic field and called it Harmonic Spatial Coherence Imaging (HSCI) [25]. Both SLSC and HSCI are based purely on the spatial coherence of backscattered echoes and do not depend on the echo magnitude. We have demonstrated through simulations that SLSC imaging performs as well as conventional B-mode imaging in detecting lesions under noise-free conditions while it dramatically improves lesion detectability in a noisy environment [24]. Sample SLSC and HSCI images of in vivo liver, heart, and kidney also show improved visibility of targets and indicate that SLSC and HSCI could have significant clinical impact [25]. In this chapter, we report the results of a pilot patient study conducted to assess the clinical performance of SLSC and HSCI in liver imaging. Image metrics (contrast and CNR) are computed for fundamental B-mode, harmonic B-mode, SLSC, and HSCI images to quantify and compare visibility of in vivo
targets across different imaging techniques. Based on our previous results, we expect SLSC and HSCI to demonstrate greater improvement in low quality fundamental and harmonic B-mode images, respectively, because acoustical noise is not present in significant amounts in high-quality B-mode images [24].

2.2 Methods

2.2.1 Short-Lag Spatial Coherence Imaging

In pulse-echo ultrasound imaging, the pulse scattered from a point in tissue spreads out as it propagates back to the transducer. The spatial coherence of the echo is a measure of how similar the echo is at any two points in space. The spatial coherence is often expressed as the spatial correlation which can be estimated by

\[
\hat{R}(m) = \frac{1}{N-m} \sum_{i=1}^{N-m} \sum_{n=n_1}^{n_2} \frac{s_i(n)s_{i+m}(n)}{\sqrt{\sum_{n=n_1}^{n_2} s_i^2(n)}}. \tag{2.1}
\]

Here, \(N\) is the total number of elements in the array, \(s_i(n)\) is the sampled signal on the \(i^{th}\) element of the array, \(n\) is a sample number in the time dimension, and the difference \(n_2 - n_1\) is typically on the order of a wavelength, in samples. \(m\) is the spatial lag given in terms of number of elements. Due to the variances of the signals \(s_i(n)\) and \(s_{i+m}(n)\) that appear in the normalizing term of the equation 2.1, the spatial correlation \(R\) does not depend on the echo magnitude.

To facilitate a better understanding of spatial coherence, the spatial correlation can be thought of as a continuous function of lag \(l\), where \(l = m/N\) to make \(R\) a function of a fraction of the transmit aperture width, with maximum lag equal to 1. An image metric,
called the short-lag spatial coherence value, $V_{slsc}$, is then defined as the integral of $\hat{R}(l)$:

$$V_{slsc} = \int_0^Q \hat{R}(l) \, dl \approx \sum_{m=1}^{M} \hat{R}(m) \Delta m$$  \tag{2.2}

where $Q$ is typically in the range of $5-30\%$ of the transmit aperture width, corresponding to the region of short lags. The approximation on the right hand side is used to implement calculation on real data. The short-lag coherence metric $V_{slsc}$ is used as the pixel brightness in the SLSC image. To construct a complete SLSC image, $V_{slsc}$ is computed according to equations 2.1 and 2.2 at every depth and image line across a field of view.

Application of the SLSC imaging method to the second-harmonic signals is called Harmonic Spatial Coherence Imaging (HSCI). Second-harmonic signals are obtained by performing either band-pass filtering [19] or pulse inversion [17] on the channel signals. It is important to note that the order of operations in HSCI is different than in harmonic B-mode imaging, where the harmonic signals are computed after the channels signals have been delayed and summed.

2.2.2 Clinical study

Unprocessed, radio-frequency (RF) ultrasound data was collected in vivo on liver vasculature, common bile duct, and other hypoechoic/anechoic hepatic structures of interest in 17 patients who were referred to the Department of Radiology, Duke University Hospital for ultrasound exam of the abdomen in the time period between September 2010 and September 2011. Both hospitalized patients and outpatients were included in the study. Written consent was obtained from all participants and the study was approved by the local Institutional Review Board.

Data was collected using a Siemens 4C1 transducer (Siemens Medical Solutions USA, Inc., Issaquah, WA) attached to a modified Siemens Acuson S2000 Ultrasound scanner (Siemens Medical Solutions USA, Inc., Issaquah, WA). The transducer used a 2.5 MHz
center frequency with a 60% fractional bandwidth. The individual channel signals needed to create SLSC and HSCI images were recorded using a custom synthetic-receive-aperture sequence in combination with the Axius Direct™ Ultrasound Research Interface [11]. The transducer had a total of 192 elements but, due to the limited system programmability, individual-channel RF data was saved for only 64 elements from 54 A-lines, where the 64 elements were centered about the transmit aperture for each beam. For comparison, conventional beamformed RF signals were acquired concurrently with the single-channel-acquisition sequence to construct full B-mode images. Full aperture (192 elements) was used on the transmit end with the transmit frequency set to 1.82 MHz and the focal depth adjusted to optimally capture the liver vasculature and other structures of interest.

Harmonic channel data was obtained using the pulse-inversion method [17]. Individual channel data was collected for positive and negative transmit pulses and the two data sets were added together to produce a harmonic channel data set. The signals obtained from the positive transmit pulse were used to construct fundamental B-mode and SLSC images. Because the single-channel acquisition sequence for harmonic data was developed after the start of the study, harmonic data was collected for the final 12 of the 17 subjects.

2.2.3 Data Processing and Statistical Analysis

SLSC and HSCI images were created from the fundamental and harmonic individual channel data, respectively, using equations 2.1 and 2.2. The size of the correlation kernel used to compute the spatial correlation function \((n_2 - n_1)\) in Eq. 2.1 was chosen to be one wavelength in order to maintain axial resolution similar to B-mode imaging and, at the same time, yield stable coherence functions. Contrast and contrast-to-noise ratio (CNR) were calculated in the B-mode and SLSC/HSCI images for the structures of interest according to the equations below:

\[
Contrast = -20 \log_{10} \left( \frac{S_i}{S_o} \right),
\]

(2.3)
In equations 2.3 and 2.4, $S_i$ and $S_o$ are the mean signal magnitudes of the same-size regions inside and outside of the lesion, respectively, and $\sigma_i^2$ and $\sigma_o^2$ are corresponding signal variances. User-selected regions inside and outside the anatomy of interest were the same for the matched B-mode and SLSC/HSCI images.

Based on contrast and CNR values, B-mode images were classified as high, medium, or poor quality. High quality images were classified as having contrast higher than 10 dB and CNR higher than 1.1. Low quality images were classified as having either contrast lower than 6 dB or CNR lower than 0.8. Any image that did not fall into one of the two categories was classified as medium quality. The above criteria were determined empirically. In our experience, high quality images had large values for both contrast and CNR, and either contrast less than 6 dB or CNR less than 0.8 (or both) were enough to result in inadequate or poor visualization of the target and yield a low quality image.

Hypothetical improvements in contrast and CNR between different imaging methods were investigated using a matched-pair t-test. To compare fundamental B-mode to SLSC, $n = 17$ matched sample pairs (from all subjects) were used to calculate the test statistic. To compare harmonic B-mode to HSCI, SLSC to HSCI, and fundamental B-mode to harmonic B-mode $n = 12$ matched sample pairs (from the subjects that had harmonic data) were used to find the test statistic. Adjusted $p$ values were calculated by using Holm-Bonferroni method to control the type I error rate arising from multiple testing [52]. Adjusted $p$ values of less than 0.05 were considered to indicate a significant difference. In addition, the magnitude of improvement was computed for each tested sample. Samples were also divided into high, medium, and poor quality images and improvements were computed for individual categories as well.
2.3 Results

Examples of matched B-mode and SLSC/HSCI images are presented in Figures 2.1 through 2.4. Because a limited amount of individual channel data can be saved to create an SLSC/HSCI image (due to programability limitations of the ultrasound scanner), the SLSC/HSCI images cover a narrower field of view than the B-mode images. For display purposes, the SLSC/HSCI images are overlayed on the corresponding B-mode images between the arrows. B-mode images are displayed on a decibel scale while a linear gray-scale colormap is used to display SLSC/HSCI images. The dynamic range of the B-mode images were chosen to optimally visualize structures of interest while the background brightness of the SLSC and HSCI images were scaled to match that of the B-mode images. The regions used to calculate the contrast and CNR are indicated by white contour lines in the B-mode images (the same regions are used in the matched SLSC/HSCI images).

Figure 2.1 demonstrates a high quality fundamental B-mode image (left) and its corresponding SLSC image (right). A large blood vessel appears at the center of field of view in both images. In the B-mode image, the lumen of the vessel contains low-level acoustic noise. In the SLSC image, the clutter in the lumen is reduced and the surrounding tissue is smoother, which results in slightly higher contrast and CNR; 13.5 dB contrast and 1.86 CNR obtained for the SLSC image compared to 11.3 dB contrast and 1.4 CNR obtained for the B-mode image.

An example of a medium quality fundamental B-mode and its corresponding SLSC image is shown in Figure 2.2. A blood vessel spanning the depth of the image at the center of field of view can be seen in both images, with the SLSC image demonstrating significant improvements in target visualization. Contrast and CNR values were calculated to be 8.9 dB and 2.05 for SLSC imaging, respectively, and 7.8 dB and 0.95 for B-mode imaging. Matched harmonic B-mode and HSCI images of the same structure in Figure 2.2 are shown in Figure 2.3. Following the criteria (for contrast and CNR) outlined in section
Figure 2.1: High quality fundamental B-mode image (left) and its matched SLSC image (right). Note that the SLSC image is the sector inserted into the B-mode image between the arrows. SLSC reduces clutter inside of blood vessels and increases smoothness of the surrounding tissue. The contrast of the large blood vessel located at the center of field of view at 10 cm depth is 11.3 dB and 13.5 dB, and the CNR is 1.4 and 1.86 for B-mode and SLSC images, respectively. The white contour lines in the B-mode image indicate the regions used to calculate contrast and CNR values.

2.2.3, the harmonic B-mode image is classified as medium quality. The overall level of noise in the image is reduced when compared to the fundamental B-mode (Figure 2.2). In the HSCI image, clutter is reduced further than in the harmonic B-mode. The CNR was found to be 2.13 for the HSCI image and 1.16 for B-mode. Contrast is comparable between the two images; 9 dB for HSCI and 9.6 dB for B-mode.

Figure 2.4 shows a poor quality fundamental B-mode and its matched SLSC image. Here, the B-mode image has diminished diagnostic value as part of the blood vessel in the center of field of view is not visible. In the SLSC image, acoustic noise is suppressed and the structure is clearly visualized. This is reflected in tremendous improvement in contrast and CNR from B-mode to SLSC. Contrast was found to be 4.44 dB for SLSC compared to 0.26 dB for B-mode imaging. CNR was estimated to be 0.79 for SLSC imaging compared to 0.03 for B-mode imaging.
Contrast and CNR values calculated from matched B-mode and SLSC/HSCI images for all patients are displayed as scatter plots in Figures 2.5 and 2.6 respectively. Data obtained from one patient is represented by a single point on the scatter plot. The ordinate of the point is the contrast/CNR value calculated from the B-mode image and the abscissa is the contrast/CNR value calculated from the matched SLSC/HSCI image. The main diagonal of the graph (denoted by the solid line) indicates where B-mode and SLSC/HSCI images yielded the same contrast/CNR. Points above the main diagonal indicate improvement in contrast/CNR from B-mode to SLSC/HSCI. Different markers are used to indicate subjects with low, medium, and high B-mode-image quality and dotted lines are used to indicate the boundaries of the contrast/CNR values used to classify B-mode images. Scatter plots are shown for both fundamental (Fig. 2.5 (a) and 2.6 (a)) and harmonic (Fig. 2.5 (b) and 2.6 (b)) data. Because there were subjects for which only the fundamental data was collected, a light gray color markers were used on the fundamental-data plots to
Figure 2.3: Harmonic B-mode image (left) and matched HSCI image (right) of the same vessel as in Figure 2.2. Even though the B-mode image is of medium quality, the HSCI image shows notable improvement in target visualization. The contrast is 9.6 dB and 9 dB and the CNR is 1.16 and 2.13 for B-mode and SLSC images, respectively.

Figure 2.4: Poor quality fundamental B-mode image (left) and matched SLSC image (right). Noise has corrupted the B-mode image and does not indicate the presence of a vessel at the center of the field of view. In the SLSC image, the vessel is easily visualized. The contrast is 0.26 dB and 4.44 dB and the CNR is 0.03 and 0.79 for B-mode and SLSC images, respectively.
In Figure 2.5, it can be seen on both plots that, with exception of a single subject, all SLSC/HSCI images have higher contrast than their B-mode counterparts. For one subject, contrast becomes slightly worse from B-mode to SLSC/HSCI. In Figure 2.6, all subjects (including both fundamental and harmonic data) demonstrate an improvement in CNR from B-mode to SLSC/HSCI. Because both contrast and CNR are used to classify B-mode images, a few points in Figures 2.5 and 2.6 appear to fall outside the contrast or CNR demarcation of low/mid/high quality.

A summary of the results in Figures 2.5 and 2.6 is provided in Tables 2.1 and 2.2. Mean values for contrast and CNR and their ranges for the different imaging methods are presented in Table 2.1. For fundamental B-mode and SLSC imaging, mean values and ranges are presented for two sets of data; the first set includes all of the subjects \((n = 17)\), and the second set includes only the subjects for which harmonic data existed.
Table 2.1: Mean and range for contrast and CNR values of hypoechoic/anechoic targets.

<table>
<thead>
<tr>
<th></th>
<th>Fundamental B-mode</th>
<th>SLSC</th>
<th>Harmonic B-mode</th>
<th>HSCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contrast (dB) mean</td>
<td>5.58</td>
<td>12.36</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>n = 17</td>
<td>range 0.26 - 12.52</td>
<td>4.44 - 29.81</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Contrast (dB) mean</td>
<td>5.14</td>
<td>11.08</td>
<td>5.76</td>
<td>9.18</td>
</tr>
<tr>
<td>n = 12</td>
<td>range 0.26 - 10.37</td>
<td>4.44 - 24.15</td>
<td>0.57 - 9.72</td>
<td>1.50 - 19.33</td>
</tr>
<tr>
<td>CNR mean</td>
<td>0.75</td>
<td>1.88</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>n = 17</td>
<td>range 0.03 - 1.39</td>
<td>0.66 - 4.56</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>CNR mean</td>
<td>0.69</td>
<td>1.82</td>
<td>0.76</td>
<td>1.70</td>
</tr>
<tr>
<td>n = 12</td>
<td>range 0.03 - 1.28</td>
<td>0.66 - 4.56</td>
<td>0.08 - 1.28</td>
<td>0.28 - 2.50</td>
</tr>
</tbody>
</table>

Table 2.2: Average improvements achieved between fundamental B-mode and SLSC and between harmonic B-mode and HSCI.

<table>
<thead>
<tr>
<th></th>
<th>Fundamental B-mode to SLSC</th>
<th>Harmonic B-mode to HSCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>B-mode quality</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>22%</td>
<td>3.4%</td>
</tr>
<tr>
<td>Medium</td>
<td>39%</td>
<td>22%</td>
</tr>
<tr>
<td>Contrast Poor</td>
<td>288%</td>
<td>137%</td>
</tr>
<tr>
<td>Overall</td>
<td>153%</td>
<td>68%</td>
</tr>
<tr>
<td>p &lt; 0.0001, n = 17</td>
<td>p &lt; 0.01, n = 12</td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>63%</td>
<td>10%</td>
</tr>
<tr>
<td>Medium</td>
<td>158%</td>
<td>102%</td>
</tr>
<tr>
<td>CNR Poor</td>
<td>533%</td>
<td>300%</td>
</tr>
<tr>
<td>Overall</td>
<td>318%</td>
<td>177%</td>
</tr>
<tr>
<td>p &lt; 0.0001, n = 17</td>
<td>p &lt; 0.001, n = 12</td>
<td></td>
</tr>
</tbody>
</table>

as well (n = 12). For harmonic B-mode and HSCI, mean values and ranges are shown for all subjects that had harmonic data (n = 12). Overall, for both contrast and CNR, SLSC obtains the highest mean values followed by HSCI, harmonic B-mode, and fundamental B-mode. Also, all of the mean values obtained for fundamental B-mode and SLSC on the subset of data (n = 12) are slightly lower than those obtained on the full set of data (n = 17) (Table 2.1).
A more detailed comparison is presented in Table 2.2 which shows average improvements (expressed as percentages) of contrast and CNR achieved between different imaging methods. For each pair of imaging methods, separate improvements for images of high, medium, and poor quality are shown in addition to the overall improvement. Due to the insufficient number of samples for some of the categories, statistical significance is shown only for the overall improvements (shown are adjusted \( p \) values and number of sample pairs, \( n \), used to calculate the test statistic). Overall, SLSC and HSCI show significant improvements in target detection when compared to fundamental and harmonic B-mode, respectively; adjusted \( p \) values are smaller than 0.001 for both contrast and CNR. In addition, the results obtained from the individual image-quality categories suggest that the improvements increase as the image quality decreases with the highest percentage improvements (between fundamental B-mode and SLSC and between harmonic B-mode and HSCI) observed for poor quality B-mode images. Also, greater improvements are observed between fundamental B-mode and SLSC than between harmonic B-mode and HSCI. The improvements between fundamental B-mode and harmonic B-mode and between HSCI and SLSC are statistically insignificant (adjusted \( p \) values are larger than 0.05 for both contrast and CNR). As such, these improvements are not reported in Table 2.2.

### 2.4 Discussion

SLSC and HSCI tend to reduce clutter and improve the overall image quality compared to B-mode liver images. As seen in the sample images (Figures 2.1 - 2.4), the most significant improvements are achieved in visualization of small-size, negative intrinsic-contrast structures such as blood vessels. While the source of contrast in B-mode images is the difference in echo brightness, the contrast in SLSC/HSCI images arises from the difference in signal coherence [24, 66]. This means that in B-mode images, incoherent signals
inside of a vessel lumen appear similar to surrounding tissue while in SLSC/HSCI images, these signals are highly suppressed. As a result, when compared to their matched B-mode images SLSC/HSCI images display crisper vessel boundaries and reduced clutter inside of a vessel lumen.

The surrounding tissue appears smoother and more uniform in SLSC/HSCI images compared to their matched B-mode images (Figures 2.1 - 2.4). We hypothesize that these differences arise because the mechanisms responsible for speckle noise in SLSC/HSCI images are different than those in B-mode images. The grainy texture of B-mode images is due to variations of the speckle brightness, resulting from the constructive and destructive interference of reflections from sub-wavelength particles. The variance of the speckle brightness increases with average echo magnitude often reaching large values [116]. Speckle noise in the SLSC/HSCI images is due to variations of the spatial coherence function, which does not depend on echo magnitude and exhibits relatively high uniformity at low lags [117].

Improvements in target visualization between fundamental B-mode images and SLSC images and between harmonic B-mode images and HSCI images are supported by statistically significant differences in target contrast and CNR. For both contrast and CNR, greater relative improvements are observed between fundamental B-mode and SLSC than between harmonic B-mode and HSCI. We hypothesize that this is due to the fact that harmonic B-mode already reduces near-field reverberation clutter, thus leaving HSCI with less incoherent signal to suppress.

Similarly, an increase in relative contrast/CNR improvements (between B-mode and SLSC/HSCI) is observed with the decrease in B-mode image-quality (Table 2.2) because lower quality B-mode images have a stronger incoherent component, meaning that the relative improvements made by SLSC/HSCI would be higher. As hypothesized, the largest improvements are seen for the poor quality B-mode images. Some B-mode image-quality categories lack the number of samples to show statistical significance of these improve-
ments. Therefore, hypothesis testing was done only for the overall improvements.

As previously stated, the results did not show significant differences (in contrast or CNR) between SLSC and HSCI and between fundamental B-mode and harmonic B-mode images. A power analysis indicated that these tests lacked power due to insufficient number of samples. As the primary focus of our study was to determine if SLSC and HSCI produced higher quality images than the delay-and-sum beamforming methods currently used in clinic and for that purpose, our sample size was sufficiently large.

This study faces several limitations. First, for all study participants, we were unable to acquire any images of focal lesions in the liver. We are aware of the importance of lesion detection/visualization in ultrasound liver imaging and acknowledge that this specific population needs to be included in order to assess the performance of SLSC/HSCI in fulfilling this task. Second, we are unable to create B-mode images that have similar high-quality displays as commercial, state-of-art US scanners because access to the sophisticated post-processing filters developed by major scanner manufacturers is not readily available. In addition, the lack of hardware/computational power that would allow faster acquisition and on-site processing of large amounts of individual-channel data prevented us from obtaining real-time feedback of SLSC/HSCI images. These issues could be alleviated with new software-based-beamforming platforms that would allow quick acquisition and access to large amounts of single-channel data. Nevertheless, the results presented here are encouraging because the improvements in blood vessel visualization demonstrate that SLSC/HSCI could be well suited for \textit{in vivo} detection of other anechoic/hypoechoic targets in the liver (such as focal lesions).

2.5 Conclusion

A study was performed that showed SLSC and HSCI imaging produce higher quality \textit{in vivo} liver images than conventional delay-and-sum beamforming methods. SLSC and
HSCI images of the livers of 17 randomly selected patients display improved visibility of blood vessels (i.e., sharper delineation of vessel walls and suppressed clutter in the vessel lumen) as well as higher uniformity of the surrounding tissue when compared to their matched B-mode images. These observations are supported by statistically significant improvements in target contrast and CNR from fundamental B-mode to SLSC and from harmonic B-mode to HSCI. In addition, the magnitude of the improvements obtained by spatial-coherence imaging increases as the quality of B-mode images decreases; the highest relative improvements are observed for poor quality fundamental B-mode images. In the future, we plan to acquire real-time SLSC/HSCI images by using a computationally powerful, software-based beamforming system. We also anticipate further exploration of clinical applications of SLSC/HSCI imaging by recruiting additional patients and conducting other task-specific studies.
3

Short-lag Spatial Coherence Imaging on Matrix Arrays: Phantom and In Vivo Validation

3.1 Introduction

High-speed volumetric ultrasound has a unique ability to provide real-time and non-invasive visualization of anatomy and pathology in three dimensions [29]. However, there are challenges associated with the small element size of typical 2-D arrays and the use of broad transmit beams that can lead to suboptimal image quality and decreased diagnostic utility of the modality. In particular, small 2-D array elements have relatively high impedance (compared to 1-D array elements) making them more susceptible to parasitic capacitance [41, 79, 102, 107]. The small element size also limits the area over which an element can receive the signal compromising that element’s sensitivity to weak echoes in a noisy in vivo environment. System sensitivity is further reduced due to the use of broad transmit beams needed to achieve real-time frame rates [100].

In [54], we extended the use of a recently developed beamforming method, short-lag spatial coherence (SLSC) imaging [66], to volumetric data in an attempt to improve image quality in clinical 3-D ultrasound. In particular, we presented a theoretical model
for applying SLSC imaging to 2-D arrays as well as simulations showing that volumetric SLSC imaging improves lesion detectability compared to conventional 3-D delay-and-sum imaging [54]. Here, we demonstrate the feasibility of volumetric SLSC imaging in vivo on a modified commercial 3-D ultrasound system.

System architecture of most clinical ultrasound scanners makes implementation of advanced beamforming methods difficult. These systems provide limited programmability of transmit waveforms and lack access to the channel echo data. In addition, for the high element-count 2-D arrays for modern 3-D ultrasound systems, partial beamforming of the subaperture data is implemented in the handle of the array in order to limit losses in sensitivity (due to impedance mismatching or parasitic capacitance), as well as to reduce cable weights and system cost [79]. The resultant inability to access radio-frequency (RF) data for each element limits the realization of many techniques requiring custom transmit sequences or advanced aperture-domain signal processing, including phase aberration correction and adaptive beamforming. Such methods have seen limited or no usage on commercial real-time 3-D systems and are difficult to evaluate in off-line studies without access to individual channel data.

Noteworthy are several implementations of phase-aberration correction algorithms on clinical 3-D ultrasound scanners using single channel data of partially beamformed sub-apertures [55, 56, 57, 75]. Ivancevich et al. [55] implemented multi-lag least-squares cross-correlation and speckle brightness algorithms and compared their performance in correcting for physical aberrators using a single sparsely-sampled 2-D array. For the speckle-brightness method, no off-line processing was used; the entire method was implemented using the scanner beamforming routines. Lindsey et al. [75] implemented a least-squares cross-correlation method on a pitch-catch setup in order to correct for phase aberration in 3-D transcranial ultrasound in vivo. Here, each matrix array was used as a correction source for the opposing array thus allowing estimation of multiple arrival time maps and reducing the error in aberration correction.

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Hyun et al. explored the performance of the SLSC method on simulated volumetric data and showed that for small 2-D subapertures, partial beamforming within subapertures does not degrade the SLSC-image quality [54]. In the following, we demonstrate the concept of volumetric SLSC imaging using phantom and in vivo liver data from a commercial matrix array and 3-D ultrasound scanner. Utilizing the system’s large-scale parallel receive processing, we collected partially-beamformed channel data from the fully-sampled matrix array at high speeds and reconstructed matched B-mode and SLSC volumes of a vessel phantom and liver vasculature off-line. Contrast and CNR are computed for the vessels of interest using complete matched volumes to compare target visibility between the two beamforming methods. Concurrently acquired 3-D Doppler data is used as a gold standard for visualizing vasculature in three dimensions.

3.2 Methods

3.2.1 Short-Lag Spatial Coherence Imaging on Matrix Arrays

The spatial coherence of a backscattered ultrasonic wave is a measure of how similar the echo is at any two points in space. It can be predicted by the Van Cittert-Zernike (VCZ) theorem as the Fourier transform of the square of transmit beam amplitude if the imaging target is diffuse scatterers [81]. Spatial coherence can be expressed as spatial correlation and further simplified to a product of two triangle functions when the diffuse scatterers are insonified with a narrowband pulse from an unapodized rectangular aperture. The spatial correlation for this case (of diffuse scatterers) has been derived in [54], and is presented here for convenience:

\[
R_{DS}(\Delta x, \Delta y) = \left(1 - \frac{\Delta x}{D_x}\right) \left(1 - \frac{\Delta y}{D_y}\right),
\]

(3.1)

In 3.1, \(\Delta x\) and \(\Delta y\) denote the distance between two points in the aperture plane, and \(D_x\) and \(D_y\) denote the transmit aperture size in the \(x\) and \(y\) dimensions, respectively. The
spatial correlation of the pressure field can be estimated from the signals of the individual elements of a matrix array as

\[
\hat{R}(i, j) = \frac{\sum_{n=n_1}^{n_2} s_i(n)s_j(n)}{\sqrt{\sum_{n=n_1}^{n_2} s_i^2(n) \sum_{n=n_1}^{n_2} s_j^2(n)}},
\]

(3.2)

where \(i\) and \(j\) are two elements on the 2-D aperture, \(s_i(n)\) and \(s_j(n)\) are the signals sampled by those elements, \(n\) is a sample number in the time dimension, and the difference \(n_2 - n_1\) represents the axial kernel length used to calculate interelement correlation and is typically on the order of a wavelength. Note that the signals \(s_i(n)\) and \(s_j(n)\) in equation 3.2 are already delayed to achieve focusing at the desired location.

To create an SLSC volume, first, a region of short lags is defined on the 2-D aperture to include all element pairs whose signals would have a correlation coefficient above some value \(P\) for the theoretical case of diffuse scatterers. In other words, for every element \(i\), a set of elements \(j\) is defined such that \(R_{DS}(x_i - x_j, y_i - y_j) \geq P, 0 < P < 1\). Then, to obtain a single SLSC voxel, \(\hat{R}(i, j)\) is computed (by applying equation 3.2 to the individual-element signals) and summed over all short-lag pairs of \(i\) and \(j\). For a complete SLSC volume, the last step is repeated at each depth for every received individual-element data set [54].

To implement volumetric SLSC imaging on a clinical matrix array, we applied the above procedure on the partially-beamformed channel data as the signals from the individual elements were not accessible.

### 3.2.2 Rapid Single Channel Acquisition

Single channel data was acquired from a 4z1c matrix array (Siemens Medical Solutions USA, Inc.). This high-element-count 2-D array has both an azimuthal pitch and an elevational pitch of 0.4 mm. Array elements are grouped in rectangular subapertures that are beamformed in the handle of the transducer giving signals for 192 system channels. In
our previous implementations [26], each channel corresponded to a single array element. Herein, data from an individual channel refers to data beamformed within a rectangular subaperture. The array was connected to a modified Siemens Acuson SC2000 scanner (Siemens Medical Solutions USA, Inc., Mountain View, CA) that has a 64:1 parallel-receive capability; i.e. it can use the channel data from one transmit event to create up to 64 receive beams in parallel.

The complex data of the individual channels were collected using a full-synthetic receive sequence, similar to the one described by Dahl et al [26]. With this method, the full aperture is used for transmit, while the signal from a subset of individual channels is collected on receive. The same transmit event is repeatedly fired until the signals for each of the channels (i.e. beamformed subapertures) are collected. Integrating this approach with parallel receive beamforming on the scanner allows for multiple channels to be acquired at one time, thus reducing the number of transmits needed to acquire a complete channel-data-set.

For the experiments described herein, a 30:1 parallel receive configuration was used to collect the data for 180 channels (total of six transmit pulses per image line) at 2.5 volumes per second. 0.4 seconds was required to obtain a complete single channel data set needed to reconstruct a full (B-mode or SLSC) volume. The complex I/Q data collected for each channel was sampled at a rate of 2.5 MHz, which was sufficient to obtain high-resolution ultrasound images.

3.2.3 Flow Phantom Experiment

The individual-channel data needed to reconstruct complete B-mode and SLSC volumes was acquired on an ATS Laboratories model 523A Doppler phantom (ATS Laboratories, Bridgeport, CT) with a 4 mm vessel, using the sequences described in the section 3.2.2. The data was acquired using a transmit frequency of 2.5 MHz and a transmit focus of 60 mm. The field of view spanned 38° in azimuth and 19.2° in elevation and was interro-
gated with 330 transmits that were fired sequentially to populate a 22 by 15 transmit-beam grid. The dense transmit-beam configuration was used to ensure that the spatial sampling was sufficient to reconstruct high-resolution B-mode and SLSC volumes.

A water-based corn-starch solution (10 g/l) was constantly flowing through the vessel while the phantom was scanned, and the conventional 3-D color Doppler volume was acquired concurrently with the individual channel data to be used as a gold standard for visualizing the vessel lumen. Because a default Doppler sequence was used on the scanner, the Doppler data was collected over a different field of view than the channel data. The Doppler field of view spanned $32^\circ$ in azimuth and $26^\circ$ in elevation and was sampled with 90 Doppler lines using a transmit frequency of 2.5 MHz. Doppler data was processed by the scanner before acquisition.

### 3.2.4 In Vivo Experiments

Individual-channel data was also collected in vivo on the liver vasculature of four human volunteers, ages 29 to 58. Written consent was obtained from all participants, and the study protocol was approved by the local Institutional Review Board. The same data acquisition sequences and imaging configuration were used as for the flow-phantom experiment (section 3.2.3). Conventional 3-D color Doppler was used for guidance and targeting of blood vessels. Color Doppler volumes were acquired concurrently with the single-channel-acquisition sequence as a gold standard for visualizing the vasculature in the region of interest (ROI).

### 3.2.5 Data processing

From the single-channel data, matched B-mode and SLSC volumes were reconstructed off-line. SLSC volumes were reconstructed following the procedure outlined in section 3.2.1 (for a more detailed description of the reconstruction methods reader is referred to the Methods section of [54]). Contrast and CNR values were computed for the vessels of
interest for complete matched volumes according to the equations 2.3 and 2.4, respectively. For the sake of clarity, both equations are reproduced below:

\[ Contrast = -20 \log_{10} \left( \frac{S_i}{S_o} \right), \]

\[ CNR = \frac{S_i - S_o}{\sqrt{\sigma_i^2 + \sigma_o^2}}. \]

\(S_i\) and \(S_o\) are the mean signal magnitudes of the regions inside and outside of the vessel, respectively, and \(\sigma_i^2\) and \(\sigma_o^2\) are corresponding signal variances. The regions outside of the vessels were selected to have the same average speckle brightness as the vessel walls. The regions inside of the vessels were selected using a Doppler mask. To create the mask, a general region containing the vessel of interest in the Doppler volume was manually selected. The dynamic range of the Doppler signal within that region was then limited to remove the noise and obtain a clean and continuous mask of the vessel lumen. To minimize the spillage of Doppler signal (mask) outside of the vessel lumen, the cutoff value for amplitude was calibrated on the vessel-phantom with the known vessel diameter. The mask was then applied to the matched B-mode and SLSC volumes.

3.3 Results

Examples of 2-D and 3-D images generated from matched B-mode, SLSC, and color-Doppler volumes are presented in Figures 3.1 through 3.6. The B-mode images are displayed on the decibel scale with the dynamic range that allows for the clearest view of the vessels of interest for a given acquisition. The SLSC images are displayed using a linear color-map with a dynamic range that has been scaled to match the background brightness of the B-mode images. The Doppler images are also displayed using a linear map but with the dynamic range and transparency adjusted (independently of the B-mode and SLSC images) to show clear and continuous Doppler signal from the vessels of interest. The red
contour lines in the 3-D Doppler images highlight the regions of the vessel lumen used to calculate contrast and CNR for the B-mode and SLSC volumes.

Figure 3.1 shows matched B-mode, SLSC, and color-Doppler volumes reconstructed from a phantom data set. For the 3-D B-mode and SLSC volumes, cutaway views are displayed (at 48° azimuth and 22° elevation angle) in order to expose a 4 mm vessel that spans the azimuth dimension of the volumes. Orthogonal slices of the volumes in Figure 3.1 are shown in Figure 3.2 and are selected to optimally display different cross-sections of the vessel. The vessel can be observed in all 2-D and 3-D images. The SLSC images demonstrate reduced acoustic noise inside the vessel lumen when compared to the corresponding B-mode images. The SLSC images also display reduced background brightness in the upper part of the field of view, which can be attributed to suppression of reverberant clutter in that region.\(^\text{1}\) Reverberant clutter appeared as parts of the aperture were not in full contact with the phantom due to the shape of the phantom and the scanning geometry employed to obtain optimal Doppler signal. The Doppler images show the vessel lumen fully populated by color-Doppler signal and the lumen boundaries can be clearly visualized. Using Doppler signal to select a 3-D region inside the blood vessel, the contrast and CNR values are calculated to be 2.27 dB and 0.34 for the B-mode volume, and 4.73 dB and 1.58 for the SLSC volume.

Examples of matching B-mode, SLSC, and color-Doppler images of \textit{in vivo} liver vasculature are shown in Figures 3.3 through 3.6. 2-D and 3-D images are created from two volumetric data-sets, both acquired from a 29 year old male volunteer, in the same general region of the liver, but at slightly different angles to demonstrate spatial stability of volumetric SLSC imaging. In order to make the vasculature fully visible in the 3-D B-mode and SLSC images, Figures 3.3 and 3.5 display cutaway views of the volume.

\(^{1}\) We previously showed [66] that the coherence curves for diffuse targets exhibit lower values in the presence of acoustic noise resulting in darker SLSC pixels/voxels. This is in contrast to B-mode images where average speckle brightness is proportional to signal variance [116] and the regions of diffuse scatterers can appear bright in the presence of clutter.
FIGURE 3.1: Left to right: B-mode, SLSC, and color-Doppler 3-D images generated from a phantom. The B-mode and SLSC images show only a part of the acquired field of view in order to expose a 4 mm vessel spanning the elevation dimension of the volumes. The SLSC image demonstrates improved visualization of the vessel cross-section compared to the matched B-mode image. The Doppler image confirms the extent of the vessel and shows clear and continuous color-Doppler signal at the location of the vessel lumen.

FIGURE 3.2: Orthogonal slices created from the volumes shown in Figure 3.1. Left to right: matched B-mode, SLSC, and color-Doppler slices in azimuth plane (top row) and elevation plane (bottom row). The SLSC slices display less clutter inside the vessel lumen and better delineation of the vessel walls than the corresponding B-mode slices. In the Doppler slices, the boundaries of the vessel lumen are clearly visualized.
3-D and 2-D images created from the first *in vivo* acquisition are presented in Figures 3.3 and 3.4, respectively. In both the B-mode and SLSC volumes of Figure 3.3, a narrow vessel spanning 6 to 9 cm depth is observed as well as a large vessel in the lower part of the field of view. In the B-mode volume, the lumen of these vessels contains low level acoustic noise. In the SLSC volume, clutter inside the large vessel is suppressed and the surrounding tissue appears smoother. Part of the narrow vessel in the SLSC volume also shows reduced clutter, but the upper region of the vessel lumen is difficult to distinguish from the surrounding tissue; this is probably because of the 3-D rendering which makes the far wall of the vessel appear like clutter. 2-D SLSC slices in Figure 3.4 indeed show that the clutter in this part of the vessel is suppressed. Using the Doppler signal to define the region inside of the narrow vessel, the contrast is calculated to be 15.32 dB and 10 dB, and the CNR is calculated to be 1.6 and 2.3 for the B-mode and SLSC volumes, respectively. The signal from the large vessel has not been captured in the Doppler volume as the clinical system used to collect the data was designed primarily for cardiac application and had difficulties detecting slower hepatic flow. The SLSC volume also shows two potential small blood vessels (denoted by black arrows) that do not appear in the B-mode and Doppler volumes. These structures can be more clearly visualized in the azimuth SLSC slice in Figure 3.4.

Figure 3.4 shows azimuth and elevation (2-D) slices of the volumes displayed in Figure 3.3. Cross-sections of the same blood vessels that are observed in both B-mode and SLSC volumes are observed in the B-mode and SLSC slices, with SLSC slices showing reduced noise inside of the vessels and improved edge definition of the vessel walls. 2-D SLSC images also display details that are not visible in their B-mode counterparts. As suggested, two potential small blood vessels are located at about 6 cm depth in the azimuth SLSC scan and are marked by white arrows for clarity. In the corresponding B-mode image, these structures are not visible due to high acoustic noise. The Doppler scans fail to confirm the presence of the small vessels but they do show the full extent of the narrow vessel located
FIGURE 3.3: Left to right: B-mode, SLSC, and color-Doppler volumes of in vivo liver vasculature. B-mode and SLSC volumes display cutaway views of the acquired volume in order to show the full extent of vessels in three dimensions. A narrow vessel spanning 6 to 9 cm depth appears in both B-mode and SLSC volumes as well as a large vessel located at the lower part of the field of view. While the SLSC volume shows reduced acoustic noise inside of the vessels compared to the B-mode volume, parts of the narrow vessel in the SLSC volume are difficult to distinguish from the surrounding tissue. The SLSC volume also indicates the presence of two small vessels at 6 cm depth (denoted by black arrows) that do not appear in B-mode and color-Doppler volumes. These structures are more clearly visualized in the azimuth SLSC slice in Figure 3.4.

at 4 to 8 cm depth.

Matched B-mode, SLSC, and color-Doppler volumes of in vivo liver vasculature, reconstructed from the second sample acquisition, are displayed in Figure 3.5. The acquired field of view captures the same blood vessels shown in Figures 3.3 and 3.4, but in the presence of high acoustic noise. In the B-mode image, the noise obscures visibility of the vessels while in the SLSC image, the noise is suppressed and the vessels are clearly visualized. For example, two narrow vessels spanning between 6 and 8 cm depth are difficult to observe in the B-mode image, but are easy to detect in the SLSC image. The Doppler image conveys the full size and shape of one of these vessels but, for the reasons mentioned previously, it does not contain the signal from other vasculature that appears in the B-mode or SLSC images. The contrast and CNR are computed for the narrow vessel whose presence is confirmed in the Doppler image. The Doppler signal is used to define the region inside the vessel. The contrast is 7.91 dB and 8.90 dB and CNR is 1.01 and 1.51
for the B-mode and SLSC volumes, respectively.

Azimuth and elevation cross sections of the volumes in Figure 3.5 are shown in Figure 3.6. Both B-mode scans are of poor quality as the tissue structures are overwritten by acoustic noise. SLSC scans reduce noise and show improved visualization of the hepatic vasculature. Specifically, cross-sections of the narrow vessels located around 6 cm depth are difficult to detect in the B-mode images but are well observed in their SLSC counterparts. The presence of one of these vessels is confirmed in the matching Doppler scans.

Image quality metrics for B-mode and SLSC volumes in Figures 3.2 through 3.6 are summarized in Table 3.1. In all examples, the SLSC volumes show higher CNR val-
FIGURE 3.5: Left to right: B-mode, SLSC, and color-Doppler volumes created from the second in vivo data-set. The 3-D images offer a different view of the same hepatic structures shown in Figures 3.3 and 3.4, but contain a significant amount of clutter. The 3-D SLSC image demonstrates reduced clutter and improved visualization of blood vessels compared to the matched B-mode image. Specifically, two narrow blood vessels spanning 6 to 8 cm depth cannot be visualized in the B-mode image, but the structures are clearly shown in the SLSC image. The shape and size of one of these vessels can also be seen in the 3-D Doppler image.

values than the matching B-mode volumes. In addition, the B-mode contrast values are in agreement with our previous in vivo measurements of clutter magnitude in anechoic/hypoechoic regions (which range from about 25 dB to about 5 dB below the mean brightness of the surrounding tissue) [68]. For the B-mode volumes created from the phantom and second in vivo acquisitions, clutter levels are high and the matching SLSC volumes demonstrate improvements in vessel contrast. For the first in vivo data-set, the B-mode volume yields higher contrast than the matched SLSC volume with contrast values being large (clutter being low) for both modalities.

3.4 Discussion

Phantom and in vivo results demonstrate the feasibility of SLSC imaging on a commercial matrix array and 3-D ultrasound scanner. SLSC images of the vessel phantom (Figures 3.1 and 3.2) convey the extent of the vessel in three dimensions, without sig-

\[2\] In [68], the magnitude of clutter was measured at different points inside of anechoic/hypoechoic regions in units of dB relative to the mean brightness of the surrounding tissue. Assuming the echogenicity of blood is significantly lower than the echogenicity of the surrounding tissue, vessel contrast can be used to approximate mean clutter magnitude inside of the vessel.
Figure 3.6: Orthogonal slices created from the volumes shown in Figure 3.5. Left to right: matched B-mode, SLSC, and color-Doppler slices in azimuth orientation (top row) and elevation orientation (bottom row). The azimuth and elevation slices indicate improved visualization of hepatic vasculature achieved by volumetric SLSC imaging compared to conventional 3-D B-mode. In particular, cross-sections of the narrow blood vessels located around 6 cm depth do not appear in the B-mode images but are clearly visible in their SLSC counterparts. The presence of one of these vessels is confirmed in the matching Doppler slices.

Significant artifacts, and using the data from a single volumetric acquisition. The in vivo data-sets (acquired in the same general region of the liver) demonstrate the stability and consistency of SLSC imaging on a matrix array; the shape and size of the blood vessels look comparable between the two SLSC volumes despite different scanning orientation used at each acquisition (Figures 3.3 and 3.5). In all examples, the SLSC volumes are re-

Table 3.1: Image quality metrics for sample phantom and in vivo acquisitions.

<table>
<thead>
<tr>
<th>Acquisition</th>
<th>Phantom</th>
<th>1st in vivo</th>
<th>2nd in vivo</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B-mode</td>
<td>SLSC</td>
<td>B-mode</td>
</tr>
<tr>
<td>Contrast (dB)</td>
<td>2.27</td>
<td>4.73</td>
<td>15.32</td>
</tr>
<tr>
<td>CNR</td>
<td>0.34</td>
<td>1.58</td>
<td>1.60</td>
</tr>
</tbody>
</table>

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constructed from the partially beamformed data. Delaying-and-summing the signals with subapertures prior to constructing the spatial coherence curves provides averaging of the channel-noise and ensures that the coherence function is sufficiently sampled in both azimuth and elevation dimensions. The improvements in contrast and CNR achieved by this hybrid SLSC imaging technique are consistent with the results demonstrated from noisy and noise-free simulations [54].

Sample 2-D and 3-D images reconstructed from the SLSC volumes show improved visibility of the vessels when compared to their B-mode counterparts (Figures 3.1 - 3.6). The SLSC imaging on a matrix array integrates the coherence function strictly over the short-lag region (in both azimuth and elevation dimensions), thus leaving out the incoherent signals present in the long-lag region [54]. Via this mechanism, the SLSC imaging suppresses incoherent echoes (and thus clutter) inside the vessels that come from the off-axis scatterers or reverberation, which enhances definition of the vessel walls [24, 66]. In a B-mode volume, the echo amplitude is displayed instead of coherence, so the incoherent echoes tend to overwrite and obscure the structures of interest. The rate of acquisition of single channel data listed in section 3.2.2 and low echogenecity of blood ensure that the observed improvements in vessel visualization in the SLSC images are not biased by the motion of blood/corn-starch solution inside of vessel during the acquisition.³

The liver tissue appears smoother and more uniform in the in vivo SLSC images than in the corresponding B-mode images (Figures 3.3 - 3.6). This smooth texture is not associated

³ Given the data acquisition rates presented in section 3.2.2 the estimated motion of blood/corn-starch solution during the acquisition of a single imaging line was 0.1 - 0.2 mm, which was unlikely to result in a substantial decorrelation of the echoes from the moving scatterers across the aperture [111]. In addition, due to low echogenecity of blood compared to the surrounding tissue (up to -30 dB [20]), contribution of these echoes to the signal received from the vessel lumen is very small compared to the off-axis scattering and reverberation from the surrounding medium. Any fluctuation in correlation of these weak echoes alone would therefore not be sufficient to cause a significant change in vessel visualization. Finally, with the single channel acquisition sequence described in section 3.2.2 data is collected on 30 channels simultaneously, which means that for majority of channels comprising the region of short lags there is no decorrelation of signal due to flow. The last statement would hold true even for the cases of high flow and high echogenecity of scatterers inside of vessel.
with the loss of resolution (or information in the image) but it is rather due to reduction in variance of SLSC pixels.\textsuperscript{4} We have demonstrated that the variance of the speckle brightness in the SLSC images is lower (than in the corresponding B-mode images) because the spatial-coherence function exhibits high uniformity (and thus low variance) in the region of short lags [117]. In addition, the hybrid SLSC imaging technique implemented on the clinical matrix array averages noise within the subapertures of the array (prior to computing the coherence curves), which further reduces the variance of SLSC speckle. As shown in simulation [54], subaperture averaging can effectively reduce speckle noise in the SLSC images even for small subaperture sizes.

Improvements in vessel visualization between B-mode and SLSC images are supported by contrast and CNR values computed for the complete B-mode and SLSC volumes (Table 3.1). Observed CNR values are in agreement with the simulation results in [54]. For example, the plots in Figure 10 (in [54]) show that CNR of a -12 dB lesion in the presence of low and medium acoustic noise (up to element SNR of -20 dB) is between 2.8 and 3.0 for the SLSC volumes formed using 8 x 8 element subapertures; CNR values for the corresponding B-mode volumes are about 1.5. These values are comparable to CNR values obtained for the B-mode and SLSC volumes from the first \textit{in vivo} acquisition (1.6 and 2.3, respectively). Further, CNR values obtained from the second \textit{in vivo} acquisition (1.01 and 1.51 for the B-mode and SLSC volumes, respectively) are within the range of values shown in plots in Figure 10 (in [54]), at high noise levels. In particular, at -20 dB element SNR, simulations predict CNR of a -12 dB lesion to be about 1.0 for B-mode and about 1.8 for hybrid SLSC imaging (implemented on 8 x 8 element subapertures).

The analysis presented in this chapter faces several limitations. First, the data was collected using a phased matrix array which was designed primarily for cardiac imaging and had a relatively small aperture. With this setup, we were unable to create B-mode

\textsuperscript{4} Our previous measurements of resolution in the SLSC images (defined as width of a point target or distance between two point targets), indicate that it is highly dependent on the level of noise and that it is not directly related to the texture size.
images that had high-resolution displays similar to those obtained with large linear arrays that are typically used in abdominal imaging. Second, the Doppler confirmation is lacking for some vessels in the in vivo acquisitions because the cardiac system used to collect the Doppler data was not calibrated to capture slower hepatic flow and acquisitions were not synchronized with the cardiac cycle (the latter causing significant discontinuities in the Doppler signal in the presence of pulsatile flow). Because contrast and CNR could be only computed for those vessels that were detected with Doppler, a more quantitative comparison between the corresponding B-mode and SLSC volumes could not be performed. Finally, visualizing the differences between the complete B-mode and SLSC volumes is limited due to the lack of an efficient way to display volumetric data. Nevertheless, the results indicate that the hybrid SLSC imaging technique as implemented on the clinical matrix array improves visualization of blood vessels in three-dimensions and they encourage its use for imaging other structures.

3.5 Conclusion

We have successfully demonstrated the concept of volumetric SLSC imaging on the clinical 3-D ultrasound scanner and matrix array. Through a series of phantom and in vivo liver experiments, we showed that 3-D and 2-D images generated from the SLSC volumes exhibit improved visualization of the vessels compared to their matched B-mode images. We used the color Doppler signal to confirm the presence of the vessels of interest and to define the 3-D regions used in contrast and CNR calculations. SLSC volumes yielded higher CNR values than the matched B-mode volumes while the contrast values were comparable between the two modalities. Our finding also showed that delaying-and-summing the signals with subapertures (of the 2-D array) prior to constructing the spatial coherence curves did not compromise the quality of SLSC images; this is in agreement with our previous simulation results. In the future, we hope to expand our single-channel-
acquisition tool to matrix arrays with larger apertures that are more suitable to abdominal imaging but also further improve data acquisition rates which would allow us to extend volumetric SLSC imaging to cardiac application.
4

Blocked Elements Signal Characteristics and Impact on Visualizing Anechoic and Hypoechoic Targets

4.1 Introduction

When imaging with ultrasound through the chest wall, it is not uncommon for parts of the array to be positioned against the ribs, preventing them from properly transmitting and/or receiving acoustic pulses [51]. Other structures such as scar tissue or air in the lungs can also introduce a high acoustic impedance mismatch and effectively block array elements, or parts of them, during an ultrasound scan [49, 121]. Blocked elements tend to significantly degrade overall image quality, limit the acoustic window, and impede visualization of the structures of interest [70]. With the development of large-aperture, high-element-count, 2-D arrays and their potential use in transthoracic imaging, detecting and compensating for the blocked elements is becoming increasingly important. In the remainder of Chapter 4, we focus on the ways to detect blocked elements and to measure their impact on visibility of anechoic targets in vivo.

The system architecture of most clinical ultrasound scanners makes it difficult to as-
sess the problem of blocked elements \textit{in vivo}. Typically, the raw echoes from individual elements can be collected from a clinical system only through custom pulse sequencing, which is difficult to realize in real-time due to limits on the internal memory size and data-transfer rates. In addition, in most high-element count 2-D arrays, signals from the individual elements are partially beamformed in the handle of the transducer [79], and are not accessible even through the custom sequencing; this prevents complete and precise characterization of blocked parts of the array. To our knowledge, there have been no \textit{in vivo} attempts to characterize signals from blocked elements and to measure image-degradation they introduce.

There have been several \textit{ex vivo} studies aimed at understanding the mechanisms and extent of image degradation in transthoracic ultrasound. Notably, Hinkelman et al. [51] measured arrival-time and energy-level fluctuations across a mechanically scanned 2-D aperture for ultrasonic wavefronts that propagated through the extracted samples of human chest-wall. The average rms values were 21.3 ns and 1.57 dB for arrival-time and energy-level fluctuations, respectively. The receive 2-D apertures were windowed to minimize parts blocked by bone and to isolate distortions introduced by soft-tissue inhomogeneities; the above-reported results are thus clinically relevant only for intercostal imaging with small arrays.

As a part of their transcostal, high-intensity, focused ultrasound (HIFU) feasibility study, Aubry et al. measured distortions of the ultrasound beam transmitted through the ribs [3]. In simulation and \textit{ex vivo} experiments, they found that waves that propagated through bone had a pressure amplitude about six times lower than waves that propagated through soft tissue (in between the ribs). Compared to the control transmit beampatterns measured in the absence of acoustic obstacles, the beampatterns associated with trans-rib imaging experienced a mean spreading in the mainlobe half-width of 1.25 mm and an increase in the sidelobe levels of up to 20 dB. However, the transducer used in the \textit{ex vivo} study was designed for HIFU experiments (transmitting at 1 MHz with 200 elements,
8 mm in diameter each) leaving it unclear to what extent the beam would be distorted in a conventional imaging setup.

In [62], Khokhlova et al. presented a more systematic analysis of intensity distributions at the focal plane of a HIFU transducer during transrib therapy. In particular, they assessed the appearance of secondary foci due to periodic structure of the ribs, the phenomenon known as focus splitting. They simulated propagation from a phased array containing 254 randomly distributed elements (7 mm in diameter each), and predicted that ribs can lead to the appearance of anywhere between one and five focal maxima, depending on the ratio of sizes of intercostal spaces and ribs. The diameter of each focus is similar to the diameter of the focal spot in the absence of ribs. In addition, the absolute intensities in the focal plane are a function of position of ribs relative to the transducer surface; maximum focus amplitude is achieved when the beam area covered by ribs is minimal. These conclusions were reached using diffraction theory and pursuing both analytic and numerical approaches. In all cases, a strong agreement was achieved between the two solutions, and with the intensity measurements from the ex vivo setup. The studies in [62] and [3] were both aimed at ultrasound therapy, and did not address the effect of beam degradation (due to blocked elements) on visibility of distributed and anechoic targets.

In this chapter, we characterize the signals on blocked elements and measure their impact on visualizing anechoic/hypoechoic targets using simulated, phantom, and in vivo data from fully sampled 2-D apertures. Utilizing the full-wave simulation tool and a commercial 3-D ultrasound system, we demonstrate methods for detecting blocked elements based on the amplitude and cross-correlation of their signals. From simulated and in vivo data we also reconstruct B-mode images of liver vasculature using receive apertures of different sizes; vessel contrast and CNR are measured to assess visibility of targets as a function of number of blocked elements in the aperture. In order to compare performance of 1-D versus 2-D arrays for transcostal imaging, the contrast/CNR measurements are obtained for receive apertures growing in one and two dimensions of the array. In Chapter
5, we continue to address the problem of blocked elements. In particular, we measure the loss of focus quality and clutter levels when imaging through the ribs with large synthetic apertures *ex vivo*. We then evaluate different beamforming schemes aimed at recovering this loss of image quality.

4.2 Methods

4.2.1 *Full-wave Simulations*

We simulated single channel data received on a fully sampled 2-D array while imaging liver intercostally. We first created a 3-D acoustic map of parts of thorax and abdomen that would be captured in an intercostal liver scan, and then we used the full-wave code developed by Pinton et al. [96] to model wave propagation through the medium, including the effects of non-linearity, attenuation, and multiple scattering (reverberation).

The 3-D acoustic map of tissue was built using the National Library of Medicine’s Visible Human data set, which provides high resolution registered optical, MRI, and CT scans of the entire male and female bodies. Following the procedure outlined in [98], each structure in the region of interest was declared as one of the six tissue types (homogeneous, fat, muscle, connective, liver, or bone tissue) and assigned appropriate values for its acoustic properties (speed of sound, density, nonlinearity, and attenuation). Acoustic properties of each tissue type were determined from the data compiled by Goss et al. [44, 45] and are listed in Table 4.1. While the reported speed of sound in bone is as high as 3000 m/s, a significantly lower value (800 m/s) was used in the simulation to allow for more efficient temporal sampling of wave propagation. The bone density was set so that the acoustic impedance mismatch between bone and soft tissue remained similar as in real tissue.

In order to simulate speckle generating targets, small local variations in speed of sound (average variation of 5% from the surrounding tissue) were introduced throughout the
Table 4.1: Acoustic properties of different tissue types used in simulation.

<table>
<thead>
<tr>
<th>Tissue</th>
<th>B/A</th>
<th>$\alpha$ (dB/MHz per cm)</th>
<th>$c_0$ (m/s)</th>
<th>$\rho_0$ (kg/cm$^3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Homogeneous</td>
<td>9.0</td>
<td>0.50</td>
<td>1540</td>
<td>1000</td>
</tr>
<tr>
<td>Fat</td>
<td>9.6</td>
<td>0.40</td>
<td>1479</td>
<td>937</td>
</tr>
<tr>
<td>Muscle</td>
<td>8.0</td>
<td>0.15</td>
<td>1550</td>
<td>1070</td>
</tr>
<tr>
<td>Connective</td>
<td>8.0</td>
<td>0.68</td>
<td>1613</td>
<td>1120</td>
</tr>
<tr>
<td>Liver</td>
<td>7.6</td>
<td>0.50</td>
<td>1570</td>
<td>1064</td>
</tr>
<tr>
<td>Bone</td>
<td>0</td>
<td>5</td>
<td>800</td>
<td>550</td>
</tr>
</tbody>
</table>

modeled medium. The resulting point scatterers had a 40 um diameter and were randomly distributed with average density of twelve scatterers per 3-D resolution cell.

To assess image degradation caused by the ribs, a spherical anechoic lesion was inserted in the liver tissue model. The lesion was created at 6 cm depth by eliminating all point scatterers within a 3.5 mm radius. In addition, a set of modified acoustic maps was created for a control case by replacing ribs with the surrounding connective tissue; the resulting maps were otherwise the same as their transcostal counterparts. Middle elevation slices of (3-D) speed-of-sound and density maps are shown in Figure 4.1 for both transcostal and control cases.

Having specified the acoustic properties of the tissue, wave propagation was simulated for transcostal and control scans. In both cases, in order to reconstruct complete B-mode images, five transmit events were simulated across the medium in the direction along the ribs (i.e. lateral dimension), similar to a diagnostic scanner operating in a linear imaging mode. The simulation code was run for each transmit event to numerically solve the full-wave equation (via FDTD method) giving the full pressure field at all times. Initial conditions for solving the equation were set by prescribing the transmit waveforms at location of the 2-D aperture. Individual channel signals were obtained by sampling the pressure field at the face of the transducer and convolving it with the axial transducer im-
pulse response. Specifically, the center frequency of transmitted waves was set at 2.5 MHz and the transducer impulse response was set to yield a fractional bandwidth of 0.5. The 2-D aperture extended 1.9 cm in lateral and 1.4 cm in elevation dimension, and was positioned so that roughly one half of it was blocked by ribs during the transcostal scan. The individual channel signals from each transmit event were used to beamform 50 receive lines to ensure sufficient sampling in the lateral dimensions.

4.2.2 Phantom Experiments

Using the sequences described in section 3.2.2, the individual-channel data needed to reconstruct complete B-mode volumes was acquired on a tissue mimicking phantom (CIRS, Norfolk, VA). A region of diffuse scatterers in the phantom was first imaged
through a piece of absorbing rubber that was placed directly underneath the array to block a part of the 2-D aperture. The absorbing rubber was then removed and the same region of phantom was imaged to collect a control data set. The data was acquired using a transmit frequency of 2.5 MHz and a transmit focus set at 60 mm. A relatively dense transmit-beam configuration was used to ensure the field-of-view (FOV) was sampled at the Nyquist frequency at the focal depth. Specifically, 330 transmits were fired sequentially to populate a 22 by 15 transmit-beam grid that spanned 38° in azimuth and 19.2° in elevation dimension.

4.2.3 In Vivo Study

Using the same sequences and imaging configuration as in 4.2.2, the individual-channel data was acquired on the liver vasculature of five human volunteers, ages 29 to 59. Written consent was obtained from all participants, and the study protocol was approved by the local Institutional Review Board. Livers were first imaged intercostally, so that parts of the 2-D aperture were blocked by the ribs. To obtain the control data (with all the transducer elements free to transmit and receive pulses), the same vasculature was also imaged subcostally, away from the ribs. In both cases, the probe was angled so that the vasculature of interest was in the middle of the FOV. To minimize the motion artifacts, the patients were asked to hold their breath and to remain still for the duration of each acquisition.

4.2.4 Data Processing and Receive Aperture Growth

For simulated, phantom, and in vivo data sets, the amplitude and the nearest-neighbors normalized cross-correlation of the individual channel signals were computed to detect blocked elements. The two quantities were averaged axially, over a 4 cm range centered around the transmit focus, and observed as functions of channel position on the receive 2-D aperture. Channels/elements were classified as blocked if their depth-averaged amplitude was -8 dB or lower (compared to the maximum channel amplitude on the 2-D aperture), and if their nearest-neighbor normalized cross-correlation was less than 0.5. The above
criteria were determined empirically. In our experience, a relative channel amplitude of -8 dB and the nearest-neighbour normalized cross-correlation of 0.5 are strong indicators that the channel is overwhelmed by noise which can result in a loss of image quality and in inadequate visualization of the target.

In order to assess the impact of blocked elements on image quality, a series of simulated and \textit{in vivo} B-mode images were created from the receive apertures growing in one and two dimensions. For each transcostal acquisition, the direction of aperture growth was chosen to provide a clear transition going from the non-blocked part of the aperture to the blocked part of the aperture. The direction of aperture growth was restricted to a single dimension (lateral or elevation) to mimic behavior of a 1-D array with partially blocked elements.\textsuperscript{1} To investigate the benefits of using a fully sampled 2-D array over a conventional 1-D array in transthoracic ultrasound, the images were also created where the receive aperture was allowed to grow in both dimensions.\textsuperscript{2} For the abdominal data sets, the receive apertures were grown in the same direction as for the corresponding transcostal acquisitions.

The orientation and position of the reconstructed B-mode slices was the same for a given acquisition and was chosen to optimally capture hypoechoic structures of interest (lesions and liver vasculature). To compare image quality across the slices, contrast and CNR of these structures were calculated for each slice, according to equations 2.3 and 2.4.

\textsuperscript{1} This procedure amounted to summing the 2-D aperture data coherently along one dimension of the array, and then growing the resulting synthetic-receive, 1-D aperture in a manner as described by Bottenus et al. [9].

\textsuperscript{2} Specifically, blocked parts of the 2-D aperture were manually segmented using the receive-channel amplitudes for the middle transmit beam (and following the criteria above). The receive aperture was grown to include all elements outside of the segmented regions first, and then gradually introduce the blocked elements within the segmented regions.
4.3 Results

4.3.1 Individual Channel Signals

The amplitude and the nearest-neighbour normalized cross-correlation of the channel signals collected on the lesion phantom are shown in Figures 4.2 and 4.3, for the control acquisition and for the acquisition through a layer of sound-absorbing rubber, respectively. The two quantities are displayed through depth for each row of receive channels in a series of images (a through l) starting with the upper most row of channels in image a. For every image, the axial range is limited to 4 cm around the Tx focus, where the nearest-neighbour cross-correlation values are expected to follow the Van-Cittert-Zernike theorem. The channel amplitude is normalized and displayed on the decibel scale with the dynamic range that allows for clear distinction between the blocked and non-blocked parts of the aperture. Normalized cross-correlation is displayed using a linear map with the dynamic range from 0 to 1.

For the control acquisition (Figure 4.2), both sets of images look uniform with the normalized cross-correlation values being relatively high (close to one). For the acquisition where a layer of rubber was blocking the right side of the array (Figure 4.3), a sharp drop in amplitude/cross-correlation is observed over this part of the aperture.

Examples of images characterizing the individual-channel signals acquired on the livers of two subjects (out of five) are presented in Figures 4.4 through 4.8. In particular, the images of channel amplitude and the nearest-neighbour normalized cross-correlation in Figures 4.4 and 4.5 are created from a transcostal and an abdominal data set, respectively, both acquired on the liver of a 59-year old male. The two quantities are shown for all rows of channels over 4 cm depth, in a similar format as in Figures 4.2 and 4.3. For the abdominal acquisition (Figure 4.4), the images indicate no significant difference between the individual-channel signals received across the aperture. For the transcostal acquisition (Figure 4.5), the amplitude and the nearest-neighbour cross-correlation are low for the
FIGURE 4.2: Amplitude (a) and the nearest-neighbour normalized cross-correlation (b) of the channel-signals collected on the lesion phantom in the control acquisition. The quantities are displayed through 4 cm of depth around the Tx focus for all channels on the 2-D aperture, a single image for each row of channels starting with the upper-most row of channels in image a. Both sets of images display relatively high values and show no significant difference across the channels.

channel-signals received on the left side of the array, which we attribute to ribs blocking that part of the aperture. Furthermore, both sets of images in Figure 4.5 show a decreasing number of blocked channels per row going from the top to the bottom of the aperture (images a to l); this indicates a diagonal orientation of the rib with respect to the array.
surface. While the images in Figures 4.4 and 4.5 are noisier than their phantom counterparts (Figures 4.2 and 4.3), the extent of the blocked part of the aperture in the transcostal acquisition can be still clearly visualized.

Figures 4.6 and 4.7 show the images of channel amplitude and the nearest-neighbour normalized cross-correlation reconstructed from the second pair of transcostal and abdominal acquisitions, in the presence of high acoustic noise. The images are formatted in the same way as in Figures 4.2 through 4.5. For the abdominal acquisition (Figure 4.6), although corrupt by noise, signals do not appear significantly different across the channels. A bright horizontal band at about 7 cm depth can be attributed to a piece of connective tissue or to a blood vessel boundary. For the transcostal acquisition (Figure 4.7), the images h through l show lower amplitude and cross-correlation values (than the other images in the figure), which suggests that those rows of channels are partially blocked by bone. Due to high levels of clutter, it is difficult to identify the individual blocked channels by visual inspection of images h through l.

The channel amplitude and the nearest-neighbour normalized cross-correlation displayed in Figures 4.6 and 4.7 are averaged through depth and are shown over the extent of the 2-D aperture in Figure 4.8, for both abdominal and transcostal data sets. Both quantities are displayed using a linear grayscale colormap, with the dynamic range from 0 to 1. For the abdominal acquisition (Figure 4.8 a)), the average amplitude and the nearest-neighbour cross-correlation exhibit high uniformity over the entire surface of the array. For the transcostal acquisition (Figure 4.8 b)), a region of dark pixels located in the lower-right corner of both images clearly shows the extent of the blocked part of the aperture and indicates a diagonal orientation of the rib. Signals received on this part of the array have 8.4 dB lower average amplitude than the signals received on the remainder of elements.

The average amplitude and the average nearest-neighbour cross-correlation of the sim-

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3 In particular, the decorrelation among the neighbouring channels in Figures 4.4 and 4.5 is attributed to in vivo clutter.
FIGURE 4.4: Amplitude (a) and the nearest-neighbour normalized cross-correlation (b) of the channel-signals collected on the liver of the first subject during an abdominal scan. The quantities are displayed as functions of depth in a similar manner as in Figures 4.2 and 4.3. Both sets of images display relatively high values and show no significant difference across the channels. Noise in the nearest-neighbour cross-correlation images is attributed to \textit{in vivo} clutter.

FIGURE 4.5: Amplitude (a) and the nearest-neighbour normalized cross-correlation (b) of the channel-signals collected on the liver of the first subject transcostally. The quantities are displayed through a range of depths around the Tx focus in a similar manner as in Figures 4.2 through 4.4. The amplitude and cross-correlation are low for the channel-signals received on the left side of the array due to ribs blocking that part of the aperture. Going from image a to l, the number of blocked channels in a row decreases suggesting diagonal orientation of the rib with respect to the array surface. Despite the presence of acoustic noise, boundaries of the blocked part of the aperture are clearly observed.

ulated channel signals are shown in Figure 4.9. The receive-channel signals are characterized for the middle Tx beam of a simulated transcostal scan, and for the matching
FIGURE 4.6: Amplitude (a) and the nearest-neighbour normalized cross-correlation (b) of the channel-signals acquired on the liver of the second subject during an abdominal scan. Both quantities are displayed in a similar format as in Figures 4.2 through 4.5. In both sets of images, no significant difference can be observed across the channels. A bright band in the lower part of images is due to a piece of connective tissue, or to a blood vessel boundary.

FIGURE 4.7: Amplitude (a) and the nearest-neighbour normalized cross-correlation (b) of the channel-signals collected on the liver of the second subject, transcostally. The quantities are displayed in a similar manner as in Figures 4.2 through 4.6. The images h through l show lower amplitude and cross-correlation values relative to other images in the figure, which indicates that a part of the array is blocked by a rib. However, due to presence of high acoustic noise, it is difficult to identify the individual blocked channels by visual inspection.

simulation where the ribs are substituted by the surrounding connective tissue (i.e. no-rib scan). The amplitude and the nearest-neighbour cross-correlation are averaged over 4 cm of depth around the Tx focus, and are displayed across the receive 2-D aperture using
**Figure 4.8:** Average amplitude (left) and average nearest-neighbour normalized cross-correlation (right) of the channel-signals collected off the 2-D array during an abdominal (a) and a transcostal (b) liver scans. The images are created by averaging through depth the channel amplitude and cross-correlation displayed in Figures 4.6 and 4.7. For the abdominal acquisition, both quantities appear relatively uniform throughout the extent of the aperture indicating echoes have been received without significant obstruction. For the transcostal acquisition, a region of low values in the bottom right corner (of both images) is attributed to a rib blocking that part of the aperture. Shape of the blocked region suggests diagonal orientation of the rib with respect to the array surface.

a linear grayscale map and the dynamic range from 0 to 1. For the no-rib scan (Figure 4.9 a)), both quantities are uniform across the array. For the (simulated) transcostal scan (Figure 4.9 b)), the top four rows of channels (that are positioned above the rib in Figure 4.1) display lower amplitude and cross-correlation values than the rest of the aperture. While there is an agreement between the amplitude and cross-correlation images for both simulations, the cross-correlation image created from the transcostal scan displays sharper boundaries of the blocked region (of the aperture) than its corresponding amplitude image.

### 4.3.2 Growing Aperture B-mode Images

Examples of B-mode images of liver reconstructed from the simulated control (i.e. no-rib⁴) and transcostal acquisitions are shown in Figures 4.10 and 4.11, respectively. In both Figures, going from left to right images are created using the receive apertures that increase in size along the elevation dimension of the array and comprise the upper 33, 67, and 100% of the total physical aperture. For the transcostal simulation, this implies that the receive aperture grows to include the blocked elements first, and the non-blocked elements

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⁴ The terms ‘no-rib’ and ‘control’ are used interchangeably in this section to refer to the simulation case in which the acoustic properties of bone were substituted with those of the surrounding connective tissue.
are gradually added afterwards at larger aperture sizes\textsuperscript{5}. All images are log-compressed and displayed using a 60 dB dynamic range, except for the 33 %-Rx-aperture image created from the transcostal simulation, which is displayed using an extended dynamic range (80 dB) to show attenuated signals at larger depths. In the 33 %-Rx-aperture transcostal image, the region inside the lesion used to compute contrast and CNR is demarcated with white dashed lines.

The lesion is visible in all images displayed for the control simulation (Figure 4.10). As the receive aperture grows, clutter inside of the lesion gets reduced, which is most apparent going from the 33 %-Rx-aperture image to the 67 %-Rx-aperture image. In the images created from the transcostal simulation (Figure 4.11), the near-field region is brighter and the signals at larger depths are more attenuated than in the matching no-rib scans. Further, in the 33 %-Rx-aperture transcostal image, which is beamformed almost exclusively using the signals from the blocked elements, the anechoic lesion at 6 cm depth cannot be observed. The lesion visibility improves as the signals from the non-blocked elements are included in the image.

\textsuperscript{5} Only for the simulated transcostal scan, the direction of receive-aperture growth was chosen to include the blocked elements first, in order to more effectively communicate their impact on image quality.
Contrast and CNR of the anechoic lesions observed in Figures 4.10 and 4.11 are plotted as functions of receive-aperture size in Figure 4.12. The two image-quality metrics are presented on the same graph using the dual-axis plots with contrast values displayed on the left y-axis and CNR values displayed on the right y-axis. Colored solid and dashed lines are used to plot the image-quality metrics for the transcostal and control simulations, respectively. The aperture size is expressed as a percentage of total number of receive elements in the array used for image reconstruction. Vertical black dashed lines indicate sizes of the receive apertures used to reconstruct images in Figures 4.10 and 4.11.

For the control simulation, both contrast and CNR increase gradually as the receive aperture grows. For the transcostal simulation, the image quality metrics stay low as the images are beamformed using only blocked elements. Specifically, as the Rx aperture grows to include 33% of total array size, contrast and CNR for the transcostal simulation increase from 2.14 dB to 3.1 dB, and from 0.34 to 0.49, respectively. Following the same change in the Rx aperture for the no-rib simulations, lesion contrast and CNR increase from 9.36 dB to 14 dB, and from 1.19 to 1.49, respectively. Lesion contrast and CNR (computed for the transcostal simulation) start to improve as the non-blocked elements are added to the Rx aperture, reaching maxima of 14.8 dB and 1.42 at the full Rx aperture.

Sample B-mode images of in vivo liver vasculature reconstructed using receive apertures of different sizes are shown in Figures 4.13 and 4.14. The images are created from the same abdominal and transcostal acquisitions used to generate Figure 4.8 with the receive apertures growing in the elevation dimension. Going from left to right the images in each figure are beamformed using the upper 8, 67, and 100% of receive array-elements. The means that for the transcostal scan, the receive aperture is started with the non-blocked elements only, and the blocked elements are added gradually at larger aperture sizes. All images are displayed on a decibel scale with the dynamic range chosen to optimally visualize vasculature of interest for a given acquisition.

Figure 4.13 shows the selected growing-aperture images created from the abdominal
**Figure 4.10:** B-mode images of liver created from the simulated transthoracic acquisition where ribs are substituted with the surrounding connective tissue (i.e. control or no-rib simulation). Left to right: images are reconstructed using the receive apertures that increase in elevation dimension and contain the upper 33, 67, and 100 % of array elements. All images are log compressed and displayed using the 60 dB dynamic range. An anechoic lesion inserted in the liver model can be observed at 6 cm depth in all images. Increasing the extent of the receive aperture reduces clutter inside the lesion and improves the definition of its edges.

acquisition. A blood vessel located at about 7 cm depth at the center of FOV is apparent for all receive-aperture sizes. The image beamformed with only 8 % of available receive elements is saturated with noise and shape of the vessel cross-section is not clearly conveyed. The image reconstructed using 67 % of available receive elements shows significantly reduced noise and improved definition of vessel boundaries compared to its 8 % counterpart. The image beamformed using all receive elements indicates even further reduction of clutter inside of the vessel lumen.
Figure 4.11: B-mode images of liver created from the simulated transcostal acquisition where a part of the aperture is blocked by a rib. Left to right: images are reconstructed using the receive apertures of the same sizes as in Figure 4.10. The Rx aperture grows to include the block elements first, and then gradually add the signals from the non-blocked elements. All images are log compressed. The 67%-Rx-aperture and the full-Rx-aperture images are displayed using a 60 dB dynamic range, while the 33%-Rx-aperture image is displayed over 80 dB of dynamic range to show signals at depths beyond 4 cm. All images show stronger near-field reverberation and more attenuation of signal at large depths than their control counterparts (Figure 4.10). The 33%-Rx-aperture image, which is reconstructed using mainly blocked elements, is dominated by noise and no structures can be identified. In the 67%-Rx-aperture image, an anechoic lesion can be observed at 6 cm depth. The image created using the full receive aperture contains more signals from the non-blocked elements and offers improved lesion visibility compared to the 67%-Rx-aperture image. A white dashed circle in the 33%-Rx-aperture image denotes the extent of the lesion in the liver model.

*In vivo* images created from the transcostal acquisition and using the same size receive apertures as images in Figure 4.13 are shown in Figure 4.14. The image reconstructed using only the upper 8% of all receive elements is overwhelmed with clutter and no hypoechoic structures can be identified. A large blood vessel can be observed at about 11 cm
Contrast and CNR of the anechoic lesions in the liver model measured as functions of the receive-aperture size during the simulated no-rib scan (dashed lines) and during the simulated transcostal acquisition (solid lines). The two image quality metrics are presented on the same graph using the dual-axis plots with contrast values displayed on the left y-axis and CNR values displayed on the right y-axis. For the control simulation, both contrast and CNR increase gradually with the receive aperture size reaching maxima of 15.9 dB and 1.58, respectively, at full aperture. For the transcostal simulation, the two image-quality metrics remain low as the receive aperture contains mainly blocked elements. Specifically, as the Rx aperture grows to reach 33% of the total array size, contrast and CNR increase by 1 dB and 0.15, respectively. For the same change in the Rx aperture for the control simulations, contrast and CNR increase by 4.6 dB and 0.4, respectively. For the transcostal simulation, as the non-blocked elements are added to the Rx aperture, contrast and CNR grow to reach maxima of 14.8 and 1.42, respectively, at full-aperture. As a reference, the vertical black dashed lines denote the sizes of the Rx-apertures used to reconstruct the displayed B-mode images (in Figures 4.10 and 4.11).

depth at the right side of FOV in the images reconstructed using 67% and 100% of the available receive aperture with the 67%-receive-aperture image displaying clearer vessel lumen and more pronounced vessel walls.

Contrast and CNR of the vessels observed in Figures 4.13 and 4.14 are plotted over a range of receive-aperture sizes in Figure 4.15. The plots are formatted in a similar manner as in Figure 4.12, with the following modifications. The image quality metrics obtained for each acquisition are plotted on a separate graph. Contrast and CNR values that correspond to the displayed B-mode images (in Figures 4.13 and 4.14) are additionally denoted with the colored circles, while the vertical black dashed lines are used to indicate the aperture size at which contrast and CNR achieve maxima for the transcostal acquisition. Furthermore, due to diagonal orientation of the rib with respect to the array surface for the
transcostal acquisition (Figure 4.14), the receive aperture was also grown along both dimensions to potentially offer improved discrimination of the blocked region. Colored solid and dashed lines are used to plot the image-quality metrics following the receive-aperture growth in one and two dimensions, respectively.

For the abdominal acquisition (Figure 4.15 left), both contrast and CNR of the vessel increase as more elements are used to beamform the images reaching maxima of 11.4 dB and 1.57, respectively, at full aperture. This trend is independent of the direction of receive aperture growth. For the transcostal acquisition (Figure 4.15 right), the two image-quality metrics improve as the receive aperture grows until noisy signals from the blocked elements are introduced. For the receive aperture growing in the elevation dimension (solid lines), maximum values of contrast and CNR are 10 dB and 1.46, respectively, and are both measured when (the upper) 66.7% of available receive aperture is used to beamform an image. When all receive elements are used in image reconstruction, contrast and CNR decrease to 9 dB and 1.36, respectively. Image-quality metrics obtained for the transcostal acquisition and receive-aperture growth in 2-D (dashed lines in the right graph of Figure 4.15) exhibit similar general behavior as their 1-D counterparts except measurements are noisier and maxima are slightly lower.

Changes in contrast and CNR following the receive-aperture growth in one and two dimensions are summarized for the abdominal and transcostal acquisitions in all five subjects in Table 4.2.
Figure 4.13: B-mode images of *in vivo* liver vasculature acquired through the abdomen and reconstructed using receive apertures of different sizes. Left to right: images are reconstructed using the receive apertures that increase in elevation dimension and contain the upper 8, 67, and 100% of array elements. All images are log compressed and displayed using the 45 dB dynamic range. A vessel located in the center of FOV at about 7 cm depth can be observed for all three receive-aperture sizes. Increasing the extent of the receive aperture reduces clutter and improves visibility of the vessel in the resulting images.

Figure 4.14: B-mode images of *in vivo* liver vasculature acquired transcostally and reconstructed using the receive apertures of the same sizes as in Figure 4.13. The receive aperture is grown to gradually transition from the non-blocked region to the blocked region of the array. All images are log compressed and displayed using the 45 dB dynamic range. When only 8% of receive elements are used, the image is overwhelmed with noise and no structures can be identified. In the 67% receive-aperture image, a large blood vessel can be observed in the right side of FOV at about 9 cm depth. The image created using the full receive aperture includes the noise from the blocked elements and displays higher levels of clutter inside of the vessel lumen compared to its 67%-receive-aperture counterpart.
Figure 4.15: Contrast and CNR as functions of the receive-aperture size for the blood vessels captured during the abdominal acquisition (left) and transcostal acquisitions (right). Colored solid and dashed lines are used to plot values for the receive apertures growing along one and two dimensions of the array, respectively. Colored circles additionally denote the values that correspond to the displayed B-mode images (in Figures 4.13 and 4.14). For the abdominal acquisition (left), both contrast and CNR increase with receive aperture size reaching maxima of 11.4 dB and 1.57, respectively, at full aperture. This trend follows both 1-D and 2-D aperture growth. For the transcostal acquisition (right), the two image-quality metrics improve as the receive aperture grows until signals from the blocked elements are included in the image. For the receive aperture growing in the elevation dimension (solid lines), contrast and CNR reach maxima of 10 dB and 1.46, respectively, at the 66.7% receive-aperture, and then decrease monotonically to 9 dB and 1.36, respectively, at full aperture. As a reference, the receive-aperture size at maximum for the transcostal acquisition is denoted by black vertical dashed line in both plots. Contrast and CNR measurements obtained for the transcostal acquisition and 2-D aperture growth (right side, colored dashed lines) are noisier and achieve lower maxima than their 1-D aperture-growth counterparts.
Table 4.2: Changes in image quality following the receive aperture growth in one and two dimensions for transcostal and abdominal acquisitions in five different patients.

<table>
<thead>
<tr>
<th>Patient number</th>
<th>Change in Contrast (%)</th>
<th>Change in CNR (%)</th>
<th>Aperture increase (% of Rx aperture)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Transcostal 1-D</td>
<td>Transcostal 2-D</td>
<td>Abdominal 1-D</td>
</tr>
<tr>
<td>1</td>
<td>-32.9</td>
<td>(^{a})</td>
<td>17.7</td>
</tr>
<tr>
<td>2</td>
<td>-17.4</td>
<td>-31.2</td>
<td>31.1</td>
</tr>
<tr>
<td>3</td>
<td>-15.9</td>
<td>\</td>
<td>36.8</td>
</tr>
<tr>
<td>4</td>
<td>-18.2</td>
<td>\</td>
<td>125.3(^{b})</td>
</tr>
<tr>
<td>5</td>
<td>-11.7</td>
<td>-22.4</td>
<td>57.4</td>
</tr>
<tr>
<td>means</td>
<td>-19.2</td>
<td>-24.1</td>
<td>35.7</td>
</tr>
<tr>
<td>std</td>
<td>8.0</td>
<td>7.6</td>
<td>16.5</td>
</tr>
</tbody>
</table>

\(^{a}\) Direction of aperture growth was chosen to yield the highest peak-contrast/CNR values for a transcostal acquisition. For some subjects, an additional degree of freedom has not changed the direction of optimal aperture growth resulting in the same peak-contrast/CNR values as for the single-dimension aperture-growth. These repeated values are not displayed to reduce clutter.

\(^{b}\) Lack of a good acoustic window through the abdomen resulted in low image quality and extremely large changes in contrast and CNR for this acquisition. These values have been treated as outliers and have not been included in mean/standard deviation calculations.
4.4 Discussion

4.4.1 Detection of Blocked Elements

Simulation, phantom, and in vivo results demonstrate that blocked elements can be detected based on low amplitude and cross-correlation values of their signals. In particular, the elements were declared as blocked if their average amplitude was -8 dB or lower (relative to the maximum channel amplitude in the aperture) and if their average nearest-neighbour cross-correlation was less than 0.5. The locations of the blocked elements in the phantom and simulation acquisitions were verified based on the (known) positions of the acoustic obstacles. Specifically, in the images of channel amplitude and the nearest-neighbour normalized cross-correlation created from the phantom acquisition through a piece of sound-absorbing rubber (Figure 4.3), the array elements that were positioned directly above the rubber (on the right side of the array) show lower values than the rest of the aperture. In a similar way, in the aperture-domain images created from the simulated transcostal scan (Figure 4.9 a)), parts of the 2-D aperture that were in the geometric shadow of a rib \(^6\) display lower amplitude and cross-correlation values than the remaining channels.

The validity of the blocked element-detection method is further confirmed with the matched control data obtained on phantoms and in simulation. When collecting the matched control data, the acoustic obstacles were removed from the wave-propagation path while the rest of imaging conditions remained the same as in the corresponding blocked-element acquisitions. For the control acquisition in a tissue-mimicking phantom, this meant that the region of diffuse scatterers was imaged without the sound-absorbing rubber in the propagation path. For the control simulations, the acoustic maps of the thorax were modified by replacing bone with the surrounding connective tissue. For both acquisitions, the resulting images of channel amplitude and the nearest neighbour cross-correlation (Figures

\(^6\) The acoustic shadow cast by ribs in the simulated transcostal scan can be predicted from the speed-of-sound and density maps in Figure 4.1.
4.2 and 4.9 a) are uniform and display high values across the channels, which confirms the absence of acoustic obstacles. This indicates that the blocked elements detected in the matching transcostal simulations/phantom experiments can be attributed only to the presence of acoustic obstacles.

The channel amplitude and cross-correlation images reconstructed from the *in vivo* acquisitions support the results obtained from the simulation and phantom experiments. The images of average channel amplitude and average nearest-neighbour cross-correlation reconstructed from an abdominal liver scan (Figure 4.8 a)) display uniformity across the channels in the absence of an acoustic obstacle. In the corresponding images created from the matching transcostal acquisition, a region of low values can be observed in the bottom right corner (Figure 4.8 b)), and is attributed to a rib blocking that part of the aperture.

The examples of aperture-domain images reconstructed from the *in vivo* scans also demonstrate that depth averaging improves blocked-element detection in the presence of high acoustic noise. The *in vivo* images that display channel amplitude and the nearest-neighbour cross-correlation as functions of depth (Figures 4.4 through 4.7) are noisier than their phantom counterparts (Figures 4.2 and 4.3). Noise in the channel data is attributed to the *in vivo* clutter and can especially affect the nearest-neighbour cross-correlation images. We have shown previously that in the presence of clutter, spatial covariance can decrease even at low lag values [66]. As the cross correlation takes on lower values, its estimates exhibit significantly higher variance according to the VCZ theorem [117]. The amplitude and cross-correlation images reconstructed from the transcostal acquisition on the second subject are corrupted with acoustic noise (Figure 4.7), and while low values indicate that part of the aperture is blocked by a rib, the individual blocked channels cannot be identified. However, after those images are averaged axially (over 4 cm depth), the extent of the blocked regions can be clearly visualized in the resulting 2-D aperture images (Figure 4.8 b)).
4.4.2 Decreased Visibility of Anechoic and Hypoechoic Targets due to Blocked Elements

Signals received on the blocked channels are overwhelmed with noise and they degrade visibility of anechoic/hypoechoic targets. The B-mode image created from the transcostal simulations using the upper 33% of the receive aperture is saturated with noise and the anechoic lesion at 6 cm depth is not visible (Figure 4.10). As observed in the corresponding channel amplitude and cross-correlation images (Figure 4.9 b)), the receive aperture used to create this B-mode is comprised almost entirely of the blocked elements. The B-mode image created from the matching control simulation with the same-size Rx aperture shows the lesion with a contrast of 9.36 dB and CNR of 1.19 (Figures 4.11 and 4.12). In addition, the contrast and CNR plots in Figure 4.12 show that the lesion visibility in the simulated transcostal scans stays low as the Rx aperture is expanded to include more blocked elements.

The B-mode images reconstructed form the in vivo acquisitions indicate that turning off blocked elements could improve contrast and CNR of the anechoic/hypoechoic targets. As observed in the B-mode images created from the transcostal acquisition in Figure 4.14, when the blocked elements are added to the Rx aperture to increase its size from 66% to 100% of the total array size, vessel contrast and CNR decrease from 10 dB to 9 dB, and from 1.46 to 1.36, respectively. Again, this is contrasted with the matching abdominal acquisition where the vessel contrast and CNR increase monotonically with the receive aperture size. Similar trends have been observed in the other four subjects. Adding signals from the blocked elements results in the mean drop in contrast of up to 24%, while the average drop in CNR (computed for the same changes in the receive apertures) is measured at 10% (Table 4.2). Excluding signals from the blocked elements in the image could therefore partially recover loses in vessel contrast and CNR.

The analysis of in vivo and simulated B-mode images presented in this Chapter faces several limitations. The images reconstructed from the transcostal acquisitions fail to
demonstrate that fully sampled 2-D apertures offer improved discrimination of the blocked regions compared to conventional 1-D arrays. In particular, the 2-D aperture growth yields larger improvements in contrast and CNR than the 1-D aperture growth only for two subjects (Table 4.2). In contrast and CNR plots created from a sample transcostal acquisition (Figure 4.15), maximum values achieved for the case of 1-D aperture growth are larger than maxima for the 2-D aperture growth, despite the diagonal orientation of the rib with respect to the array surface (Figure 4.8). This can be attributed to the fact that the size and location of the blocked regions change with the Tx beam direction, and that this kind of variation makes it difficult to track smaller changes in contrast and CNR. One way to improve discrimination of blocked regions (in matrix arrays) would be to grow the receive apertures independently for each transmit beam.

There are several discrepancies between the trends observed in simulated and in vivo B-mode images. The difference in lesion contrast and CNR between the simulated transcostal and control images (reconstructed using the full Rx aperture) is not as large as the corresponding difference between the in vivo transcostal and abdominal images. Further, unlike the in vivo images created from the abdominal acquisitions, the B-mode images created from the control (no-rib) simulation do not show significant changes in lesion visibility for the larger receive-aperture sizes. These (unexpected) trends in simulation results can be paritally attributed to crude tissue models employed. For example, inhomogeneities in subcutaneous tissue are roughly sampled, and ribs are presented as uniform regions of bone tissue, while in reality, they have a more layered structure. In addition, contrast and CNR measurements can vary depending on a particular realization of speckle, and the simulation measurements ought to be averaged over multiple realizations to allow for a fair comparison with the in vivo results.
5

Blocked Element Compensation Methods as applied to Large Coherent Apertures

5.1 Introduction

The use of large apertures in medical ultrasound has the potential to improve image resolution and visibility of anechoic and hypoechoic targets at larger depths. However, when imaging through the ribs, acoustic obstacles and inhomogeneities can cause diminishing returns for increasing aperture size. Large apertures are more susceptible to partial blockage by bone. In addition, wavefront distortions induced by intercostal soft tissues can make it difficult to preserve signal coherence across large array surfaces. Both mechanisms can degrade the quality of transthoracic scans and diminish diagnostic utility of increased aperture size.

In Chapter 4, we described simulation and in vivo studies where we imaged liver vasculature transcostally using a clinical 2-D array. We demonstrated a method to detect elements blocked by ribs and to measure the resulting loss of vessel contrast and CNR. Here, we apply blocked-element detection to large synthetic aperture data acquired through rib samples ex vivo, and we evaluate different beamforming methods aimed at recovering the
loss of image quality.

Several methods have been proposed for alleviating beam degradation during high-intensity, focused ultrasound (HIFU) treatment through the ribs [3, 6, 7, 21]. In time-reversal mirror (or phase-conjugation\(^1\)) [3, 7, 21], signals from a point source located at the focus are recorded, time-reversed, and re-emitted on each element. Alternatively, instead of assigning a range of amplitude and phase values across the transducer surface, elements located in the geometric shadow of ribs are turned off while the remaining transmit elements are uniformly weighted; this is referred to as a geometric approach in [7]. The time-reversal method accounts for diffraction effects and distributed tissue inhomogeneities making it more effective (than geometric approach) at reducing sidelobe levels at the focal plane and energy deposited on ribs. However, it requires the physical presence of a point source at the focus, or modeling wave propagation from a point source using CT or MRI data.

In an \textit{ex vivo} experiment, Aubry et al. applied the time-reversal mirror to focus the transmit beam behind a sample of porcine ribs [3]. The correction resulted in a 5 dB decrease in sidelobes, while the ratio between the energy delivered at the target location to the total emitted energy increased six times. As a part of the same study, the geometric approach was simulated with qualitatively similar results, except the energy-increase at the target location was 13\% lower than for the time-reversal mirror. Bobkova et al. compared geometric and time-reversal-based compensation methods directly in simulation, for an idealized radiator [7]. Both approaches yielded approximately a two-fold increase in intensity at the focus (compared to no-compensation), while the time-reversal resulted in less energy deposited on the ribs than the geometric approach; power loss on the ribs was 1, 7.5, and 58\% for the time-reversal, geometric compensation, and no-compensation, respectively. An upgraded version of time-reversal compensation scheme involved de-

\(^1\) The time reversal method is applied to the pulsed beams while the phase conjugation method is used for continuous wave transmit.
composition of a time-reversal operator (DORT method) and was proposed by Cohard et al. [21].

To improve the efficacy of a transcostal HIFU treatment, Ballard et al. implemented adaptive refocusing on a dual-mode (imaging plus therapy) array [6]. Complex weights for the array elements were computed by solving a constrained optimization problem where the goal was to maximize the intensity at the target location and minimize the intensity across the ribs. Images obtained with the array were used to infer locations of the ribs and target. In an \textit{ex vivo} setup that utilized a Plexiglas ribs phantom, the desired changes in energy distribution after refocusing were confirmed through the direct temperature measurements and through changes in echogenecity of the images.

An adaptive beamforming method for improving the quality of transthoracic images was developed by Li et al. [70]. They used the information from multiple receive beams to estimate locations and amplitudes of acoustic sources and to suppress the undesired sidelobe contributions. The estimates were obtained via the method of total least squares, and as such were robust to the imperfections in the model. The approach by Li et al. was effective in improving phantom images of point-targets and distributed targets but the additional complexity of bimodal targets prevented its \textit{in vivo} implementation. In all experiments, the elements blocked by ribs were labeled as missing and were not used in image formation.

In Chapter 4, we presented a method to detect blocked elements, and we measured image degradation they cause while trying to visualize anechoic and hypoechoic targets \textit{in vivo}. In the following, we apply the blocked-element detection and compensation to large synthetic apertures while imaging point targets through canine rib samples \textit{ex vivo}. Specifically, large synthetic transmit and receive apertures spanning across multiple ribs are created by collecting the channel data from a fully sampled clinical matrix array at multiple and known array locations. To improve image quality, blocked elements are detected and retroactively turned off, while the apertures covering intercostal spaces are either com-
pounded, or coherently summed using uniform and adaptive channel-weighting schemes. Clutter levels and point spread functions are measured to evaluate the compensation methods, and to assess the effect of aperture size on image quality. As a reference, some of the beamforming schemes are also applied to synthetic aperture data collected through a section of canine abdomen, in the absence of acoustic obstacles. Arrival-time surfaces are reconstructed for all acquisitions to estimate the tissue-induced aberration, and to offer further means to understand and compensate for the loss of focus quality in transthoracic imaging.

5.2 Methods

5.2.1 Large Coherent 2-D Aperture Acquisitions

Large coherent 2-D aperture data sets were created by collecting full synthetic data from a Siemens 4z1c matrix array (Siemens Medical Solutions USA, Inc.) at multiple and known array positions. This high-element-count 2-D array has a 1.92 cm-by-1.44 cm aperture footprint and a pitch of 0.4 mm in both dimensions. Array elements are grouped in square subapertures that are beamformed in the handle of the transducer giving signals for 192 system channels. While in the previous work [26] each channel corresponded to a single array element, herein data from an individual channel refers to data beamformed within a rectangular subaperture. With the full synthetic sequence, signals are collected for each transmit/receive pair of channels. The array was connected to a modified Siemens Acuson SC2000 scanner (Siemens Medical Solutions USA, Inc., Mountain View, CA) that has a 64:1 parallel-receive capability which was used to increase acquisition rate of channel signals as described in (Section) [58].

The 4z1c array was positioned using a high-precision motorized translation stage setup that provided four degrees of freedom. Specifically, the setup consisted of three linear translation stages arranged orthogonally to one another (2 x Newport UTM100, 1 x Newport
ILS100, Newport Corporation, Santa Clara, CA), and of a rotation stage (Newport URS50) that allowed the transducer to be rotated around its elevation axis. The accuracy of the linear translation stages was better than 5 um and their unidirectional repeatability was better than 1.5 um. The rotation stage had a specified accuracy of 0.03°, unidirectional repeatability of 0.002°, and could provide a range of motion of 180°. By adjusting the angle of rotation around its elevation axis, the transducer could be mechanically steered to image the same region of interest from different lateral locations. The translation stage assembly was fixed on a portable cart, on top of a 21''x 10''x 8'' fiberglass water tank.

![Figure 5.1: Transducer locations used to collect large synthetic aperture data (a) and geometry of an individual 4x1c aperture (b). Dashed lines indicate look-direction at each transducer position; they all intersect at the point-target location (denoted with a red circle). Adjacent apertures overlap by half-of-the-transducer length. The resulting synthetic aperture is three times longer than an individual 4x1c aperture.](image)

For the experiments described herein, the full synthetic aperture data was collected
at five lateral transducer positions spaced half-of-the-transducer length apart. At each position, the transducer was mechanically steered towards the region of interest. This ensured that Tx beams fired from individual channels at different array positions achieved maximum overlap necessary to synthesize high resolution images. Synthetic Tx/Rx data from different array positions was summed to increase the lateral extent of the physical aperture (1.92 x 1.44 cm) and generate a large virtual aperture (5.76 x 1.44 cm). The geometry of the setup employed to collect large synthetic aperture data as well as geometry of an individual 4z1c aperture are shown in schematics in Figure 5.1.

5.2.2 Ex vivo Experiments

Using sequences and setup described in section 5.2.1, large coherent 2-D aperture data was acquired on a custom-designed point target phantom. The phantom consisted of a sapphire sphere 0.2 mm in diameter that was suspended in a slab of gelatin. The phantom was imaged through freshly excised sections of canine chest wall, and through a section of canine abdomen. For each acquisition, the tissue samples were placed directly underneath the array. Both phantom and the tissue were immersed in a tank filled with the (10:1) mixture of water and n-propanol that had speed of sound of approximately 1540 m/s. 170 g of salt was added to 19 liters of mixture to make it osmotically neutral and preserve the internal tissue structure. For the transcostal acquisitions, the rib samples were oriented with respect to the direction of transducer translation in such a way so that the resulting large synthetic apertures spanned across multiple ribs. After each tissue acquisition, a control data-set was acquired as well by imaging the phantom through a water-alcohol path only. All the data was acquired using a transmit frequency of 2.5 MHz. A photo of the imaging setup taken during a transcostal acquisition is shown in Figure 5.2. It is followed by the close-up views of ribs and abdomen samples in Figure 5.3.

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2 The exact amounts of water, alcohol, and salt used in the mixture were based on the models presented in [1, 80, 125].

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Figure 5.2: Experimental setup photographed during a transcostal acquisition. The 4z1c array is fixed in a transducer holder and its position is controlled via translation stages (not captured in the photo). A section of canine chest wall (containing skin, fat, ribs, and connective tissue) is placed directly underneath the array. The point target phantom is fixed to the bottom of the tank using rubber suction cups.

Figure 5.3: Samples of canine ribs (a) and abdomen (b) used in the large synthetic aperture acquisitions. The samples are sutured to a plastic mount whose arced shape ensures full contact between the transducer surface and the tissue at each (transducer) position. Bottom view of the chest-wall sample indicates that the transducer sweeps across multiple ribs during the transcostal acquisition.

5.2.3 Blocked-element Detection and Compensation

To detect blocked elements, radio-frequency (RF) signals from large synthetic apertures were summed coherently across transmit channels to create focused transmit beams. Channel amplitude and the nearest-neighbor normalized cross-correlation were then computed across the resulting synthetic receive apertures. The two quantities were averaged over 3 mm depth around axial location of the point target, and also between the overlapping parts of individual physical apertures. Channels with an average amplitude of -9 dB or less (with respect to the maximum channel amplitude on the synthetic receive aperture) were classified as blocked. This cutoff value was determined empirically.
To assess the impact of aperture size and (blocked-element) compensation methods on image quality, B-mode images of point targets were beamformed using all, and subsets of channels from the large synthetic aperture data sets. Specifically, for the transcostal acquisitions, the images were beamformed:

1) by coherent summation of all channels,

2) by applying uniform weighting and coherent summation to the non-blocked channels only,

3) by applying adaptive weighting (and coherent summation) to the individual, non-blocked Tx/Rx channel pairs,

4) and by compounding the intercostal sub-apertures.

In particular, for the adaptive blocked-element compensation, phase-aberration correction was applied along with rescaling of the available Tx/Rx channel-pairs to recover the attenuated spatial frequencies. This method is presented in greater detail in section 5.2.4.

The PSFs created from the abdominal acquisition were used to indicate performance of the beamforming methods under less severe imaging conditions. Due to the lack of blocked elements, only full synthetic aperture and compounding were applied to the channel data. For each tissue image, a matching control image was created using the same subsets of channels from the corresponding water-path acquisitions. Image quality was characterized by full-width at half-maximum (FWHM) and side-lobe levels (SLL) of the point spread functions, and by average clutter levels in the near-field.

5.2.4 Adaptive re-weighting of K-space

To adaptively compensate for the blocked channels, the remaining Tx/Rx channel pairs were weighted to recover attenuated k-space frequencies and reduce associated side-lobes in the PSF. The weights were determined following the convolution model of k-space outlined by Walker and Trahey [118].
We start with the equation (3) in [118], which is reproduced here for convenience:

\[ S\left(k_x, k_z, \frac{2z_f}{c}\right) = \frac{G}{k_z^2} A_{tx} \left(-\frac{2z_f}{f_c} \frac{k_x}{k_z}, -ck_z/2\right) \ast A_{rx} \left(-\frac{2z_f}{f_c} \frac{k_x}{k_z}, -ck_z/2\right). \]  

(5.1)

In equation 5.1, \( S\left(k_x, k_z, \frac{2z_f}{c}\right) \) is the system response at lateral and axial spatial frequencies \( k_x \) and \( k_z \), respectively, \( z_f \) is the axial location of interest, \( G \) is a scaling term that accounts for target reflectivity, \( A_{tx} \) and \( A_{rx} \) are the transmit and receive aperture weighing functions, respectively, and \( \ast \) denotes the convolution operator. If further analysis is confined to focal depth, and to center transmit frequency, the dependencies of aperture functions \( A_{tx} \) and \( A_{rx} \), and the system response \( S_{tx,rx} \) on \( k_z \) and \( z_f \) can be omitted and the equation 5.1 can be simplified to

\[ S(k_x) = \frac{G}{f_c^2} A_{tx} \left(-\frac{2z_f}{f_c} k_x\right) \ast A_{rx} \left(-\frac{2z_f}{f_c} k_x\right). \]  

(5.2)

In equation 5.2, \( f_c \) stands for the center transmit frequency and \( z_f \) is now the focal depth.

While equation 5.2 applies to arbitrary aperture functions, we approached the compensation problem by considering a simple-case scenario. In particular, if the transducer channels are assumed to be infinitesimal, for a single pair of Tx and Rx channels, the corresponding aperture functions and the resulting k-space response of the system can be written as

\[ A_{tx} = \delta(x_{1,tx}), \]  

(5.3a)

\[ A_{rx} = \delta(x_{1,rx}), \]  

(5.3b)

\[ S_{tx,rx}(k_x) = W \delta(x_{1,tx} + x_{1,rx}), \]  

(5.3c)

where \( x_1 \) denotes coordinate in the aperture plane and \( x_{1,tx} \) and \( x_{1,rx} \) are particular locations of the Tx and Rx channels in the aperture, respectively, \( W = \frac{G}{f_c^2} \) is the weighting constant, and \( k_x = \frac{x_1 f_c}{2z_f} \).
The k-space response of a multichannel system can be described as a sum of responses from the individual Tx/Rx channel pairs:

\[
S_{\text{total}}(k_x) = \sum_{tx,rx} S_{tx,rx}(l) \mid x_{1,tx} + x_{1,rx} = l,
\]

where 5.4

where \( S_{tx,rx} \) is rewritten as a function of sum of positions of Tx and Rx channels in the aperture, \( l \), and \( k_x = -l f_c / 2z_f \). If the weighting constant \( W \) is assumed to be the same across the aperture, then the total response \( S_{\text{total}}(k_x) \) is proportional to the number of available Tx/Rx channel pairs at frequency \( k_x \). In a case of a missing (blocked) Tx/Rx channel pair, the lack of its k-space response can be compensated by rescaling the remaining channel-pair responses (at that frequency). In particular, the rescaling factor at spatial frequency \( k_x \) is computed as

\[
R_S(k_x) = \frac{S_{\text{total}}(k_x)}{S_{\text{available}}(k_x)},
\]

where \( S_{\text{available}}(k_x) \) and \( S_{\text{total}}(k_x) \) are the k-space responses of the apertures with and without blocked channels, respectively.

To determine the individual channel-pair weights for the data acquisition setup described in section 5.2.1, the k-space response for the large synthetic aperture was computed from the individual physical apertures by utilizing the shifting property of convolution [65]. First, blocked channels were detected following the procedure outlined in section 5.2.3. The blocked-channel maps for the individual apertures were then auto-convolved and their respective k-space responses were shifted according to

\[
S(k_x + 2\Delta x_1 \frac{f_c}{2z_f}) = A_{tx}(x_1 + \Delta x_1) \ast A_{rx}(x_1 + \Delta x_1).
\]

As stated in section 5.2.1, \( \Delta x_1 \) in equation 5.6 was incremented in half-of-the-transducer length. The shifted k-space responses of the individual apertures were summed together to synthesize a large-aperture k-space response. The rescaling factor was determined at each
spatial frequency of this response via equation 5.5. The weights for the channel-pairs in the large synthetic aperture were re-mapped to the channel-pairs in individual apertures. To ensure that the rescaled channel-pairs were adding in-phase and could recover attenuated frequencies, the arrival-time profiles estimated in section 5.2.5 for the transcostal acquisition were applied to the non-blocked channels first.

5.2.5 Arrival-time Estimates

The large synthetic aperture data-sets collected on point targets through the ribs and abdomen were also used to estimate the shape and magnitude of the respective tissue induced aberrations. The arrival-time profiles were estimated from the channel data using a least-squares method. In the first step, focal delays were applied to the individual-channel signals to correct for geometric path-length differences in the direction of the point target. Each signal associated with a pair of transmit and receive channels could then be modeled as a delayed version of the transmitted waveform $\psi$, corrupted with some additive noise

$$s_{tx,rx}(t) = \psi(t + \delta_{tx,rx}) + \epsilon_{chan}. \quad (5.7)$$

In equation 5.7, the signal $s_{tx,rx}$ is in its time-continuous form, $\delta_{tx,rx}$ is a tissue-induced delay associated with the pair of transmit and receive channels, and $\epsilon_{chan}$ accounts for random-noise due to channel electronics. To find delays $\delta_{tx,rx}$, the discrete signals were cross-correlated with an estimate of the transmitted waveform

$$r_{tx,rx}(m) = \sum_{n=n_1}^{n_2} s_{tx,rx}(n + m) \hat{\psi}(n). \quad (5.8)$$

In Equation 5.8, $n$ and $m$ are a sample number and lag value in time dimension, respectively, and the difference $n_2 - n_1$ is on the order of wavelength. The reference waveform $\hat{\psi}$ was obtained by averaging the focused point-target signals received across the aperture.
in the control experiment. The channel signals $s_{tx,rx}$ were temporally weighted by a
decaying exponential centered around the estimated point-target depth. A 3-by-3-channel
moving-average window was also applied across the synthetic transmit aperture to reduce
the channel noise and improve cross-correlation estimates.

For each signal, the delay $\delta_{tx,rx}$ was estimated as the time-lag corresponding to the
maximum cross-correlation value

$$d_{tx,rx} = \hat{\delta}_{tx,rx} = \arg \max_m r_{tx,rx}(m) \cdot T_s \tag{5.9}$$

where $d_{tx,rx}$ and $T_s$ are used to denote the delay-estimate and sampling interval of the
signal, respectively. The measured signal delay can be expressed in terms of individual
delays on transmit and receive channels:

$$d_{tx,rx} = (t_{tx} + t_{rx}) - 2t_c + \varepsilon_d, \tag{5.10}$$

$$d_{tx,rx} = (t_{tx} - t_c) + (t_{rx} - t_c) + \varepsilon_d, \tag{5.11}$$

$$d_{tx,rx} = \Delta t_{tx} + \Delta t_{rx} + \varepsilon_d, \tag{5.12}$$

In equations 5.10 through 5.12, $t_{tx}$ and $t_{rx}$ are times for a pulse to travel from the transmit
channel (to the point target), and (from the point target) to the receive channel, respectively,
$2t_c$ is the time of flight extracted from the reference waveform, and $\Delta t_{tx}$ and $\Delta t_{rx}$ are the
tissue-induced delays on associated Tx and Rx channels that need to be estimated. $\varepsilon_d$ is
a random delay-error caused by noise in the cross-correlation estimate. The equations for
all Tx/Rx channel-pairs can be written in the matrix form as

$$\begin{bmatrix}
2 & 0 & 0 & 0 & \ldots & 0 \\
1 & 1 & 0 & 0 & \ldots & 0 \\
1 & 0 & 1 & 0 & \ldots & 0 \\
\vdots & & & & & \\
0 & 0 & 0 & 0 & \ldots & 2
\end{bmatrix}
\begin{bmatrix}
\Delta t_1 \\
\Delta t_2 \\
\Delta t_3 \\
\vdots \\
\Delta t_{192}
\end{bmatrix}
+ 
\begin{bmatrix}
\varepsilon_{1,1} \\
\varepsilon_{1,2} \\
\varepsilon_{1,3} \\
\vdots \\
\varepsilon_{180,192}
\end{bmatrix}
= 
\begin{bmatrix}
d_{1,1} \\
d_{1,2} \\
d_{1,3} \\
\vdots \\
d_{180,192}
\end{bmatrix}, \tag{5.13}$$

$$M \quad \Delta t \quad \varepsilon \quad d$$

$$(180 \cdot 192) \times 192 \quad 192 \times 1 \quad (180 \cdot 192) \times 1 \quad (180 \cdot 192) \times 1$$

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where each row of model matrix $M$ encodes a Tx/Rx channel pair, vectors $d$ and $\varepsilon$ contain all measured signal delays and associated errors, respectively, and vector $\Delta t$ contains tissue-induced delays for each channel. The dimensions of each vector and the matrix are written underneath their respective symbols. The vector $\Delta t$ was estimated via the least-squares solution

$$\hat{\Delta t} = (M^T M)^{-1} M^T d. \quad (5.14)$$

The Equations 5.8 through 5.14 were applied at each of the five physical-aperture positions using the same reference waveform $\hat{\psi}$. For the transcostal acquisition, blocked channels were excluded from the arrival-time estimates. Arrival times estimates were also obtained for wavefronts propagating through a water/alcohol-path only. These control estimates were subtracted from the tissue estimates to obtain true aberrator profiles.

5.3 Results

5.3.1 Aperture-domain Signals

Signal information obtained from the individual channels of large synthetic apertures is presented in Figures 5.4 through 5.6. Figure 5.4 shows channel amplitude and the nearest-neighbor normalized cross-correlation for sample point-target acquisitions through excised sections of canine ribs and abdomen, and for a control (point-target) acquisition through the water path only. For all acquisitions, the two quantities are averaged over 3 mm depth around axial location of the point target, and also between the overlapping parts of physical (transducer) apertures. A moving-average window is applied to the resulting quantities across the large synthetic apertures to further reduce the noise.\(^3\) Channel amplitude is displayed on the decibel scale with the dynamic range adjusted to indicate the presence of blocked elements. Cross-correlation is displayed using a linear color-map with the

\(^3\) Synthetic Tx and Rx aperture data was collected at five overlapping lateral transducer locations. Apertures spanning the physical transducer surface at each of the five locations are referred to as physical apertures. An aperture spanning all five overlapping transducer positions is referred to as a large synthetic aperture. For more information on the SA data collection method, refer to section 5.2.1.
dynamic range from 0 to 1.

Two dark regions span along the elevation dimension in the amplitude and cross-correlation images created from the transcostal acquisition; they are attributed to two ribs blocking corresponding parts of the synthetic aperture. The shape of the blocked regions is closely matched between the two images. Signal amplitude in the blocked regions is on average 8 dB lower than the amplitude recorded on the remainder of the (virtual) array. Overall, the amplitude and cross-correlation images created from the control and abdominal acquisitions display a significantly higher degree of uniformity than their transcostal counterparts. Lack of low values throughout the extent of the apertures implies that in both cases, echoes have been received on all channels without significant obstruction. Only a slight decrease in amplitude/cross-correlation, possibly due to a piece of connective tissue, can be observed in the left side of synthetic aperture for the abdominal data set.

Binary aperture maps created by thresholding the channel amplitudes for the transcostal acquisition in Figure 5.4 are shown in Figure 5.5. Channels with an average amplitude of -9 dB or less (with respect to the maximum channel amplitude on the synthetic 2-D aperture) are classified as blocked and are indicated in black color in the maps. The top map shows positions of the blocked channels in the large synthetic aperture. The bottom five maps are used to show positions of the blocked channels in the corresponding individual physical apertures.

In the large synthetic aperture map, the chosen amplitude cutoff confines the blocked channels to two regions that are observed in the corresponding amplitude and cross-correlation images (Figure 5.4). The two regions combined occupy about a third of the total synthetic-aperture size (x channels). In the physical aperture maps, shapes of the blocked regions match between the overlapping parts of the apertures.\(^4\) The size of the blocked regions varies between the individual apertures depending on their lateral location.

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\(^4\) The physical aperture maps are created from the positions of blocked channels in the large synthetic aperture. Overlapping parts of the individual apertures are therefore mapped using the same channel positions from the large synthetic aperture.
on the chest-wall sample; the second, third, and fifth apertures are only partially blocked on a single end, while the fourth physical aperture is centered on a rib and is almost completely blocked.

The k-space responses of large synthetic apertures with and without blocked channels are shown in Figure 5.6. In all spectra, the spatial-frequency axes are expressed in terms of shift indices associated with auto-convolution of the large 2-D aperture. All spectra are normalized by the maximum of the desired response in b), and are displayed using a linear color-map from 0 to 1. To create the k-space spectrum in Figure 5.6 a), the individual aperture maps in Figure 5.5 were autoconvolved, so that each spatial frequency is weighted by the number of available Tx/Rx channel pairs at the corresponding shift value\(^5\). Due to presence of blocked channels, large regions of k-space in a) experience significant attenuation. The k-space response of the equivalent synthetic aperture setup in the absence of blocked channels is shown in Figure 5.6 b). The spectrum in b) has the shape of a trapezoid in the lateral frequency dimension and the shape of a triangle in the elevation frequency dimension. Figure 5.6 c) shows the k-space response obtained after rescaling of the available Tx/Rx channel pairs in a), in order to compensate for the blocked channels and approximate the desired response in b). Due to severe blockage, at some spatial frequencies there are no available Tx/Rx channel pairs and the holes in k-space remain.

\(^5\) For more information on how the large-aperture k-space spectra are created, the reader is referred to section 5.2.4.
Figure 5.4: The amplitude (top row) and nearest-neighbor normalized cross-correlation (bottom row) of the channel signals received across large synthetic 2-D apertures during an *ex vivo* transcostal acquisition (a), during its corresponding control acquisition (b), and during an abdominal acquisition (c). For all acquisitions, the synthetic aperture spans 5.76 cm (48 channels) in lateral and 1.44 cm (12 channels) in elevation dimension. Both amplitude and cross-correlation are averaged over 3 mm depth and a low-pass spatial filter is applied over the extent of the aperture to further reduce the noise. Channel amplitude is displayed on the decibel scale from -11 to 0, while cross-correlation is displayed using a linear color-map with the dynamic range from 0 to 1. For the transcostal acquisition, regions of low values are attributed to ribs blocking those parts of the aperture. Shape of the blocked regions matches between the amplitude and cross-correlation images. For the control acquisition, amplitude and cross-correlation display high values throughout the extent of the aperture indicating echoes have been received on all channels without significant obstruction. For the abdominal acquisition, there is a slight loss of channel amplitude/cross-correlation on the left side of the synthetic aperture, potentially caused by a piece of connective tissue.
**Figure 5.5 (preceding page):** Binary aperture maps obtained by thresholding channel amplitudes for the transcostal acquisition displayed in Figure 5.4 (the upper left image). Black color is used to indicate positions of blocked channels in the full synthetic aperture (top map) and in the individual physical-transducer apertures that are used to create the synthetic aperture (bottom five maps).

![Binary Aperture Maps](image1)

**Figure 5.6:** The system response in k-space derived from the binary aperture maps in Figure 5.5 (a), the matching k-space response in the absence of blocked elements (b), and the k-space response obtained after rescaling of the non-blocked Tx/Rx channel-pairs in a) to approximate the desired response in b) (c). All images are normalized by the maximum of the desired k-space response in b), and are displayed on a linear scale from 0 to 1. Spatial frequencies in x and y axes are expressed as shift-indices associated with the auto-convolution of the large 2-D aperture. Blocked channels cause a loss of spatial-frequency amplitudes. At spatial frequencies for which all the corresponding Tx/Rx channel-pairs are blocked, holes in k-space remain after rescaling.
5.3.2 Compensated B-mode images

Examples of B-mode images of point targets and reverberation clutter reconstructed from the large synthetic aperture data are shown together with the supporting plots in Figures 5.7 through 5.16. The images are created from the same transcostal and abdominal acquisitions as the images of channel amplitude and cross-correlation in Figure 5.4. All B-mode images are reconstructed in the plane of transducer motion, along the lateral dimension at zero elevation coordinate (i.e. middle lateral slices). Since the elevation dimension of the synthetic aperture is four times smaller (than its lateral dimension), and is parallel to the ribs for the transcostal acquisition, the analysis of the point-spread functions in this dimension does not offer any new insights and is omitted. The B-mode images are displayed on the decibel scale with the dynamic range from -50 to 0.

Point target images created from the transcostal acquisition and its corresponding control are presented in Figures 5.7 and 5.8. The images from the transcostal acquisition in Figure 5.7 are created, from left to right:

1) by coherently summing signals from all the channels (full synthetic aperture method),
2) by applying uniform weighting and coherent summation to the non-blocked channels only (synthetic aperture with basic compensation),
3) by turning off the blocked channels, and applying phase-aberration correction and rescaling to the non-blocked Tx/Rx channel-pairs to approximate a desired response in k-space (synthetic aperture with adaptive compensation), and
4) by compounding the apertures that span the intercostal spaces.

For all compensation methods, the blocked channels are identified and turned off following the maps in Figure 5.5. For the adaptive compensation method, phase-aberration correction is implemented using the arrival-time profile in Figure 5.17, top. The control images in Figure 5.7 are beamformed using the same methods and subsets of channels as their corresponding transcostal images, but from the synthetic aperture data acquired through
Figure 5.7: B-mode images of point targets created with and without different blocked-element compensation schemes applied to the channel data from the transcostal acquisition (top) and from the control acquisition (bottom). For the transcostal acquisition, images are reconstructed, from left to right: by coherently summing signals from all the channels (synthetic aperture method), by applying uniform weighting and coherent summation to non-blocked channels only (synthetic aperture with basic compensation), by phase-correcting and adaptively weighting non-blocked channel signals to approximate a desired response in k-space (synthetic aperture with adaptive compensation), and by compounding the apertures that span intercostal spaces. For the latter three beamforming methods, the blocked channels are selectively turned off on both Tx and Rx following the maps in Figure 5.5. For the control acquisition, point target images are beamformed using the same methods and subsets of channels as for the transcostal acquisition. The PSFs created from the transcostal acquisition show higher sidelobes and are wider than their control counterparts. For the transcostal acquisition, just turning off the blocked channels does not significantly alter the shape of the synthetic aperture PSF. For both data sets, adaptive blocked-element compensation significantly reduces sidelobes induced by aperture sparsity. Compounding also reduces sidelobes but at the expense of increased mainlobe width for both acquisitions. All images are displayed on the decibel scale with the dynamic range from -50 to 0.

The individual images used for compounding for both acquisitions are shown in Figure 5.8; the resulting compounded images are displayed again to allow side-by-side comparison. To further facilitate comparison of the point-spread-functions (PSF) across beamforming methods and aperture sizes, the corresponding beamplots are presented in Figure 5.9.\(^6\)

The PSFs created from the transcostal acquisition show significantly higher sidelobe levels (SLL) and larger effective full-width at half maximum (FWHM) than their control counterparts. In particular, for the full synthetic aperture PSFs, going from the control to the transcostal acquisition, SLL increases by 15.1 dB and FWHM increases by a factor of 6.2\(^7\). Further, when the uniform channel-weighting is applied to transcostal data, the

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\(^6\) Beamplots refer to lateral amplitude profiles taken at the point target depth.

\(^7\) Such a large increase in the effective width of the full-synthetic-aperture PSF is due to high sidelobes in
FIGURE 5.8: Point-target images created from the individual intercostal subapertures together with the resulting compounded image (top), and the images created from the matching subsets of channels in the corresponding control data set (bottom).

FIGURE 5.9: Beamplots created from the 2-D PSFs in Figure 5.7, for the transcostal acquisition (left) and for the corresponding control acquisition (right). To highlight key results for the control acquisition, the corresponding adaptive compensation beamplot is denoted by dashed line, and the single-aperture and compounded-aperture beamplots are omitted. For the transcostal acquisition, the synthetic aperture beamplots created with and without blocked channels look almost identical if uniform weighting is applied. Side-lobes of these beamplots are higher than -6 dB and their effective width is comparable to the width of the corresponding single-aperture and compounded beamplots. For the control acquisition, turning off channels without compensation raises sidelobes to -6.3 dB. For both data-sets, adaptive compensation effectively alleviates sidelobe levels caused by aperture sparsity.
sets, the adaptive compensation (phase-aberration correction in combination with k-space rescaling) significantly reduces SLL induced by aperture sparsity, from -6.3 dB to -18.9 dB for the control acquisition, and from -2.5 dB to -7 dB for the transcostal acquisition. Compounding also reduces SLL for both acquisitions, but at the expense of FWHM. For the transcostal acquisition, the PSFs created from the second intercostal sub-aperture and from the (compensated and uncompensated) synthetic apertures with uniform weights applied all have similar effective FWHM. For the control acquisition, the full SA PSF is 3.8 times narrower than the middle sub-aperture PSFs.

B-mode images of clutter caused by propagation through the chest-wall sample are presented along with the corresponding plots of average signal amplitude in Figures 5.10 through 5.12. The images in Figures 5.10 and 5.11 are beamformed using the same methods as the point-target images in Figures 5.7 and 5.8, top rows. All images and plots are normalized by the maxima of the corresponding PSFs and are displayed on the decibel scale. In all cases, clutter levels decrease with depth. In Figure 5.10, the average clutter magnitude in the uncompensated image decreases from -17 dB at 25 mm depth to -35 dB at 70 mm depth. The images reconstructed using basic compensation and adaptive compensation methods both display reduction of clutter by about 5 dB compared to the uncompensated image, at all depths. The compounded image shows clutter level reduced by 3 dB on average. In addition, the compounded image displays smoother speckle pattern than any of the synthetic aperture images. Average clutter levels vary among the individual images used for compounding. The image beamformed using the middle intercostal sub-aperture yields a similar (relative) clutter level as the SA image created from all intercostal sub-apertures (i.e. synthetic aperture with basic compensation).

Point-target images reconstructed from the abdominal acquisition and its respective control are shown in Figure 5.13. For both acquisitions, the images are reconstructed from left to right, by summing all channel-signals coherently (synthetic aperture image), by summing signals from the middle part of synthetic aperture only (single aperture im-
Figure 5.10: B-mode images displaying clutter levels before and after blocked-element compensation is applied to the synthetic aperture data acquired through a ribs sample. The transcostal acquisition and beamforming schemes used to create images match those of Figure 5.7. In all cases, clutter magnitude decreases moving away from the ribs. Compounded and synthetic aperture images beamformed without the blocked channels show reduced clutter compared to the (synthetic aperture) image beamformed using all the channels. All images are displayed on the decibel scale with the dynamic range from -50 to 0.

The corresponding beamplots are presented in Figure 5.14. The PSFs created from the abdominal acquisition show small changes compared to their matching control images; SLL changes are within 5 dB while the mainlobe width increases at most by a factor of 1.2. For both acquisitions, the mainlobe is the narrowest in the synthetic aperture image while the single-aperture and compounded images display similar mainlobe width. Going from the single aperture to synthetic aperture images mainlobe width decreases by a factor of 3.4 for the control acquisition and by a factor of 2.7 for the

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8 The shape of subapertures used to create the single-aperture and compounded images matches the intercostal spaces, plus the adjacent blocked channels, from a transcostal acquisition. This allows for a direct comparison between the point target images generated from the abdominal and transcostal acquisitions.
Figure 5.11: Individual B-mode images of clutter used to create the compounded image in Figure 5.10, which is displayed again for clarity. Each image is normalized with respect to the maximum brightness value of the compounded point target image (the top leftmost image in Figure 5.8). In all cases, clutter magnitude decreases moving away from the ribs. The image generated from the second intercostal aperture contributes the highest amount of clutter to the compounded image.

Figures 5.15 and 5.16 show B-mode images of clutter due to propagation through the section of abdominal wall, and supporting plots of average clutter magnitude as a function of depth, respectively. The B-mode images (and their respective plots) are reconstructed using the same subsets of channels as the point target images in Figure 5.13. Overall, the clutter levels are relatively low, not exceeding -40 dB at 20 mm depth and monotonically decreasing. The compounded image displays the highest level of clutter; its average clutter magnitude is about 5 dB higher than that of the synthetic aperture and single aperture images.
**Figure 5.12:** Average signal amplitudes as functions of depth for B-mode images displayed in Figures 5.10 (left) and 5.11 (right). For each of the clutter images, signal amplitude is averaged in the lateral dimension and the average signal is normalized with respect to the maximum brightness of the corresponding point target image (Figures 5.7 and 5.8). In all plots, clutter magnitude decreases with depth. Turning blocked channels off suppresses clutter, with coherent summation of the remaining channels yielding less clutter than compounding of the intercostal apertures. Basic and adaptive compensation schemes result in similar levels of clutter. Relative clutter levels vary between the individual intercostal apertures. The image beamformed using the second intercostal aperture yields similar (relative) clutter magnitude as the images resulting from coherent summation of all non-blocked channels.

FWHM and SLL of the PSFs in Figures 5.13 and 5.7 are reported in Table 5.1, along with the PSFs created from the second transcostal acquisition and its corresponding control. Due to different tissue-sample geometries, the point targets were not imaged at the same depth, so the reported FWHM values cannot be compared directly across the tissue acquisitions. Nevertheless, a strong agreement can be observed between the two transcostal acquisitions regarding the trends across the beamforming methods; the single-aperture PSFs show the largest FWHM, and the non-compensated PSFs are almost of the same width as the PSFs formed using basic blocked-element compensation. In addition, all transcostal PSFs, except for the SAAC PSF, are significantly wider than their control counterparts; the adaptive compensation brings down the effective PSF-width close to the non-blocked levels. The SLL values are not depth-dependent and are remarkably similar between the two transcostal acquisitions; the lowest SLL are reported for the single-aperture and compounded PSFs. The PSFs created from the abdominal acquisition are only slightly wider than the corresponding control PSFs, and show significantly lower
**Figure 5.13:** Point-target images created using different subsets of channels from a large synthetic aperture data set collected through the abdomen (top) and from the data collected in the corresponding control acquisition (bottom). For both acquisitions, images are reconstructed, from left to right: by coherently summing signals from all the channels (synthetic aperture method), by coherently summing signals from the middle part of the synthetic aperture only, and by compounding the apertures that match intercostal spaces in the corresponding transcostal acquisition. The images reconstructed from the abdominal acquisition display slightly higher sidelobe levels than the corresponding control images. For both acquisitions, the middle (sub)aperture and compounded images show increased mainlobe width compared to the full synthetic aperture images. All images are displayed on the decibel scale with the dynamic range from -50 to 0.

**Figure 5.14:** Beamplots created from the 2-D PSFs in Figure 5.13, for the abdominal acquisition (left) and for its corresponding control acquisition (right). While beamplots created from the abdominal acquisition appear asymmetric and distorted compared to their control counterparts, the mainlobe width and the sidelobe levels do not change significantly between the two acquisitions. For both acquisitions, the compounded and single-aperture beamplots have similar mainlobe width; the beamwidth is the smallest for the synthetic aperture plots.

SLL compared to their transcostal counterparts.
\textbf{Figure 5.15}: B-mode images showing near-field clutter caused by (wave) propagation through the abdominal layer during a synthetic aperture acquisition. The images are beamformed using the same acquisition and subsets of channels as in Figure 5.13, top row, and are displayed on the decibel scale with the dynamic range from -50 to 0. In all images, clutter magnitude decreases with depth. The compounded image shows the most clutter while the synthetic aperture and the middle (sub)aperture images display similar clutter levels, especially beyond 20 mm depth.
FIGURE 5.16: Average clutter magnitude as a function of depth for B-mode images in Figure 5.15. For each image of clutter, the magnitude is integrated along the lateral dimension and is normalized with respect to the maximum brightness of the corresponding point target image (Figure 5.13). The compounded image yields the highest level of clutter. Relative clutter levels measured in the full synthetic aperture image are almost the same as those in the middle-aperture image. For all beamforming methods, the clutter magnitude is monotonically decreasing and does not exceed -30 dB.
Table 5.1: Assessment of PSFs across beamforming schemes and aperture sizes, for the large synthetic aperture data collected through the samples of ribs, abdomen, and in their corresponding control acquisitions (denoted with t, a, and c, respectively). For each acquisition, the PSFs are created via the synthetic aperture method (SA), via synthetic aperture with the blocked channels turned off (SA with basic compensation or SABC), via adaptively weighing the non-blocked Tx/Rx channel-pairs (SA with adaptive compensation or SAAC), from the middle part of the large synthetic array (single aperture), and by compounding (abbreviated as comp).

<table>
<thead>
<tr>
<th>Acquisition number</th>
<th>FWHM (mm)</th>
<th>SLL (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SA</td>
<td>SABC</td>
</tr>
<tr>
<td>t1</td>
<td>4.41</td>
<td>4.32</td>
</tr>
<tr>
<td>c1a</td>
<td>0.71</td>
<td>0.71</td>
</tr>
<tr>
<td>t2</td>
<td>1.93</td>
<td>1.92</td>
</tr>
<tr>
<td>c2a,b</td>
<td>0.54</td>
<td>0.48</td>
</tr>
<tr>
<td>a1</td>
<td>0.67</td>
<td>\</td>
</tr>
<tr>
<td>c3b</td>
<td>0.54</td>
<td>\</td>
</tr>
</tbody>
</table>

For the control acquisitions c1 and c2, point targets are not imaged at the same depth due to different geometries of the tissue samples in the corresponding transcostal acquisitions (t1 and t2). For each pair of tissue/control acquisitions imaging depth is the same.

The PSFs under c2 and c3 acquisitions are reconstructed from the same control data but using different subsets of channels. For SABC, SAAC, and compounded PSFs from the c2 acquisition channels are selectively turned off to create subapertures that match the intercostal spaces of the corresponding transcostal (t2) acquisition. Since the abdominal (a1) acquisition does not suffer from blocked channels, no channels are turned off for the control PSFs under c3 acquisition.
5.3.3 Arrival-time Profiles

Time-of-arrival estimates for the wavefronts originating from a point target and propagating through samples of ribs, abdomen, and water-path only are shown in Figure 5.17. The estimates are obtained across large synthetic apertures and from the same acquisitions used to create images of channel data and B-mode images in Sections 5.3.1 and 5.3.2, respectively. For all acquisitions, the synthetic receive aperture is composed of five overlapping physical aperture positions and it spans 48 channels in the lateral and 12 channels in the elevation dimension. The color of arrival-time surface is mapped to the surface height with low negative values colored in dark blue and high positive values colored in bright red.

For the transcostal acquisition, the blocked channels are omitted from the arrival-time profile following the binary maps in Figure 5.5. The arrival-time surface over the intercostal spaces indicates a high magnitude, low frequency aberrator. The estimated aberrator for the abdominal wall is of lower magnitude than its intercostal counterpart, except for the peak-estimate on the left side of synthetic array. Wavefront distortions due to propagation through water only are minimal as seen in the control profile. The root-mean-square (rms) values of arrival-time profiles are computed to be 58 ns for the transcostal acquisition, 24.8 ns for the abdominal acquisition, and 10.8 ns for the control acquisition at the transmit frequency of 2.5 MHz. For all acquisitions, there is a strong agreement between the arrival-time estimates from the overlapping aperture positions.
Figure 5.17: 2-D arrival-time profiles from a point target estimated with the large synthetic apertures during a transcostal acquisition (top), a control acquisition (middle), and an abdominal acquisition (bottom). For all acquisitions, the synthetic aperture is composed of five overlapping physical aperture positions and it spans 48 channels in the lateral and 12 channels in the elevation dimension. Color of the arrival-time surfaces corresponds to the surface height with low negative values colored in dark blue and high positive values colored in bright red. x and y axes are in units of aperture channel numbers while z axes is expressed in seconds. For the transcostal acquisition, blocked channels (as indicated in binary maps in Figure 5.5) are excluded from the arrival-time estimates resulting in the surface discontinuities. Arrival-time estimates on the remaining channels indicate that aberrations due to the intercostal spaces are dominated by low frequency components and are more severe than aberrations induced by the abdominal wall. For all acquisitions, there is a strong agreement between the arrival-time estimates from the overlapping aperture positions.
5.4  Discussion

5.4.1  Blocked-element Detection in Large Coherent Apertures

The point-spread functions and arrival-time profiles demonstrate that large transmit and receive apertures have been successfully synthesized from the individual transducer apertures at different lateral positions. The full-synthetic-aperture PSFs created from the control acquisitions are symmetric and display reduced mainlobe width when compared to their individual-aperture counterparts (Figures 5.9 and 5.14). In addition, for all acquisitions, there is a strong agreement between the arrival-time estimates obtained from the overlapping parts of individual apertures (Figure 5.17). Both observations confirm correct spatial registration of individual transducer apertures and adequate geometric delays applied to all channel signals.

Blocked-element detection algorithm introduced in Chapter 4 has been successfully applied to large synthetic apertures used to image through rib samples \textit{ex vivo}. The large-aperture binary map in Figure 5.5, which was created by thresholding the channel-amplitude image for the transcostal acquisition in Figure 5.4 clearly conveys the extent of the regions blocked by bone. On the other hand, the channel-amplitude and cross-correlation images created from the abdominal and control acquisitions display relative uniformity in the absence of acoustic obstacles (Figure 5.4); thresholding them is not expected to discriminate any signal features on the 2-D aperture.

5.4.2  Image Degradation due to Blocked Elements

Comparing clutter levels and PSFs across the tissue acquisitions and their respective controls, ultrasound propagation through the chest wall causes significantly more image degradation than propagation through the abdomen. Reverberation clutter due to chest wall is measured to be approximately -20 dB at 2 cm away from the tissue, and is 20-25 dB higher (depending on the depth) than its abdominal counterpart (Figures 5.12 and
Further, comparing the uncompensated transcostal PSFs to the full SA PSFs from the matching control acquisitions, SLL increases by as much as 15.1 dB, putting it above -6 dB for both transcostal acquisitions (Figure 5.9 and Table 5.1). As a result, the effective FWHM of the uncompensated transcostal PSFs is four to six times larger than their mainlobe width, and than the FWHM of the above-mentioned control PSFs. In contrast, wave propagation through the abdomen causes sidelobes (of the full SA PSF) to increase by 5.4 dB and the FWHM to increase by a factor of 1.2 (Figure 5.14 and Table 5.1).

Sparsity of the aperture due to blocked elements is estimated as a dominant source of high SLL for the transcostal acquisitions. To isolate the degradation of focus due to blocked elements from the effects of phase aberration, reverberation, and other sources of acoustic noise, the blocked-channel map in Figure 5.5 was used to turn off channels in the corresponding control acquisition. The resulting increase in SLL is 11.3 dB, which makes up majority of the total increase in SLL measured for the transcostal acquisition (15.1 dB) (Figures 5.7 and 5.9 and Table 5.1). For the imaged rib configuration (and the resulting distribution of blocked channels), appearance of two sidelobes of such high magnitude is consistent with the simulation and ex vivo results presented in [62] and [7].

For large arrays that employ conventional beamforming, aperture sparsity due to periodic rib structure can forfeit expected improvements in resolution. Going from a single-intercostal-subaperture PSF to the full SA PSF, SLL increases by at least 13 dB and the effective FWHM decreases by a factor of 1.3 and 2.4 for the first and second transcostal acquisitions, respectively (Figure 5.9 and Table 5.1). In contrast, for the abdominal acquisition, in the absence of acoustic obstacles, the decrease in FWHM is comparable to the increase in overall aperture size while SLL does not change significantly in the process. Comparing the PSF reconstructed using the middle third of the aperture to the full SA PSF, FWHM decreases by a factor of 2.7 while SLL stays close to -20 dB (Figure 5.14 and Table 5.1).

In particular, according to simulations results in [62], when the aperture captures multiple ribs, and width of a rib and the intercostal space are almost identical, the number of maxima observed in the beampattern will be three, one at the focus and one at each side. Furthermore, side peaks are estimated at -4 dB.
5.4.3 Impact of Phase Aberration

While phase aberration due to chest wall is not the main contributor to the loss of focus quality in transcostal ultrasound, it is significantly stronger than its abdominal counterpart. The rms values of arrival-time profiles are 58 ns for the transcostal acquisition and 24.8 ns for the abdominal acquisition (Figure 5.17). The rms arrival-time value obtained for the transcostal acquisition is much larger than the average rms value reported by Hinkelman et al. [51]. In addition to using different types of tissue for the ex vivo measurements (canine vs. human chest-wall samples), discrepancy in results can be explained by the choice of tissue-regions over which the arrival-time profiles are reconstructed in each study. The arrival-time estimates in Figure 5.17 are particularly large near the blocked channels reaching extrema of ±100 ns, which can be attributed to cartilage and connective tissue surrounding the bone. In [51], the receive apertures are windowed specifically to omit areas over bone and costal cartilage, and to isolate distortions introduced by soft-tissue inhomogeneities. As most of the arrival-time measurements are made near the center of intercostal spaces the average rms value is lower.

5.4.4 Efficacy of Compensation Methods

We have demonstrated that adaptive blocked-element compensation (i.e. phase aberration correction in combination with k-space rescaling) has a potential to reduce near-field clutter and restore point-resolution of large apertures in the presence of blocked elements. Turning off blocked channels in transmit and receive apertures reduces clutter noise in transthoracic images by as much as 5 dB, when the (remaining) intercostal sub-apertures are coherently summed (Figures 5.10 and 5.12). Further, in the presence of aperture sparsity, adaptive weighing of the non-blocked channels rescales attenuated k-space frequen-

\[10\] Hinkelman et al. measured the arrival-time fluctuations in 16 intercostal spaces to obtain the average rms value of 21.3 ns [51].
cies and reduces SLL by 5 dB for the transcostal acquisition, and by 12.6 dB for its matching control acquisition (Figure 5.7 and Table 5.1). For the transcostal acquisition, bringing the SLL below -6 dB (to -7 dB in this case) restores the effective width of the PSF to the FWHM of its mainlobe, which implies a 6-fold improvement in lateral resolution (Table 5.1). Side-lobe reduction via k-space rescaling is not as effective for the transcostal acquisition as it is for the control, since acoustic noise on the non-blocked channels introduces random variations in the k-space spectrum (of the sparse aperture) [118], making it more difficult to approximate the desired response. Phase-aberration correction only partially addresses this problem.

Other compensation methods yield partial improvements of image quality. When the blocked channels are turned off and the non-blocked channels are uniformly weighted (i.e. basic compensation), the PSFs remain virtually unchanged. This can be attributed to lower signal-amplitude on the blocked channels; while turning off those channels will reduce the noise level, it will not significantly impact the shape of higher amplitude mainlobe and sidelobes. Compounding the intercostal sub-apertures results in partial reduction of clutter; measured decrease in average clutter level for the transcostal acquisition in Figure 5.10 is about 3 dB. However, speckle/noise texture in the compounded images appears smoother than in the matching synthetic aperture images. In addition, compounding the associated PSFs reduces sidelobes significantly, and only at the slight expense of the effective FWHM. Comparing the compounded PSFs to their uncompensated counterparts, SLL decreases by no less than 16 dB while the effective FWHM increases at most by a factor of 1.4 (Table 5.1).

Observed changes in the clutter levels and of the PSF due to compounding of the intercostal sub-apertures are supported by the findings in literature. While compounding is not expected to improve the resolution significantly beyond that of the individual (sub-aperture) images, it is expected to increase the speckle SNR; compounding $N$ independent speckle realizations increases the speckle SNR by a factor of $\sqrt{N}$ [13]. In addition, the
clutter magnitude is expected to be higher in a compounded image than in the corresponding SA image, as the incoherent summation of complex random variables is larger than (or equal to \(^{11}\)) their coherent summation.

5.5 Conclusion

The blocked-element compensation was successfully realized on large coherent 2-D apertures while imaging through the excised sections of canine chest wall. The elements blocked by ribs were first detected by thresholding the average amplitudes of their signals, in a similar manner as in Chapter 4. Synthetic transmit and receive data was then used to implement different blocked-element compensation schemes offline, and to estimate the individual sources of image degradation in transthoracic ultrasound. As a reference, some of the beamforming schemes were also applied to synthetic aperture data collected through a section of canine abdomen, in the absence of acoustic obstacles. Ultrasound propagation through the chest wall results in higher clutter levels and significantly increased loss of focus quality compared to propagation through the abdomen. Phase aberration due to intercostal spaces and a periodic distribution of blocked elements (i.e. aperture sparsity) both degrade the transcostal PSF, but the latter is the main cause of excessively high SLL and can diminish the expected improvements in resolution with large apertures.

As a part of compensation, turning off the blocked channels reduces near-field clutter when the remaining channel signals are summed coherently. When uniform weighing of the non-blocked channels is used in the process, the PSF stays nearly the same as in the non-compensated case. Adaptive reweighing of the non-blocked channels to rescale the attenuated spatial frequencies has a potential to significantly reduce SLL and restore the resolution of large arrays. The adaptive compensation method is sensitive to the presence of acoustic noise and should be used in combination with the phase-aberration correction.

\(^{11}\) The incoherent and coherent summations of ultrasound signals are equal only for the case of a point target at the focus, when all the individual signals are in-phase.
(and/or other noise-reduction techniques) to ensure efficient side-lobe reduction.
The dissertation presents a number of beamforming strategies to improve the quality of ultrasound images in the presence of clutter and acoustic obstacles. A beamforming method based on spatial coherence of the received pressure fields, SLSC imaging, is shown to effectively suppress in vivo clutter and bring statistically significant improvements in visualizing liver vasculature over conventional B-mode imaging. The concept of SLSC imaging is extended to matrix arrays, and the first in vivo demonstration of volumetric SLSC imaging on a clinical ultrasound system is presented as well. Further, the dissertation offers a thorough assessment of the problem of blocked elements in transthoracic ultrasound. Methods to detect the elements blocked by ribs and to compensate for the resulting loss of image quality are evaluated in simulation, ex vivo, and in vivo experiments. With the exception of Chapter 2, all beamforming methods are intended for fully sampled 2-D apertures.

Results from the in vivo liver studies in Chapters 2 and 3 demonstrate improvements in image quality achieved with SLSC imaging (relative to matching B-mode) on 1-D and 2-D arrays, respectively. The research presented in Chapter 2 is a natural extension of
the SLSC work in [24, 25, 66], and its importance is two-fold. First, the number of pa-
tients in the pilot study (17) is sufficient to show that the improvements in visualization
of anechoic/hypoechoic targets achieved with SLSC imaging are statistically significant.
Second, the study indicates that SLSC imaging brings the largest improvements to poor
quality B-mode images, thus further adding to method’s clinical value.

Results in Chapter 3 have broader implications on 3-D ultrasound imaging with matrix
arrays. Volumetric SLSC imaging offers improved visualization of anechoic targets and
could potentially compensate for the low sensitivity associated with most of commercial
matrix arrays. In addition, the results in Chapter 3 show that subaperture beamforming
does not have a significant adverse effect on the quality of SLSC volumes, and that im-
plementation of an advanced beamforming algorithm on a clinical matrix array is feasible.
Both observations could lead to increased use of matrix arrays in the clinic.

Chapters 4 and 5 demonstrate the blocked-element detection and compensation on
2-D arrays. As indicated by both ex vivo and in vivo results, blocked elements can be
detected by thresholding their (depth-averaged) amplitudes. Turning off blocked elements
has a potential to reduce near field clutter and improve visibility of anechoic/hypoechoic
targets. Chapter 5 addresses the problem of blocked elements on large 2-D apertures. The
presence of blocked elements can lead to increased SLL which can diminish resolution
improvements expected with large arrays. The non-blocked elements have to be adaptively
weighted to suppress the sidelobes (due to aperture sparsity) and recover the resolution
accuracy of a large aperture.

While problems of reverberation clutter and blocked elements are addressed individ-
ually, they often appear together to plague image quality, especially in transthoracic ul-
trasound. Hence, in addition to turning off blocked elements, other clutter suppression
techniques could be used to help restore image quality. In particular, SLSC imaging could
be applied to improve contrast and CNR of distributed anechoic/hypoechoic targets in the
presence of blocked elements. Unfortunately, due to hardware limitations at the time of
writing the dissertation, these types of targets could not be imaged using large synthetic apertures. In addition, the non-blocked portions of the physical 2-D apertures used for transcostal imaging of \textit{in vivo} liver vasculature in Chapter 4 were too small to expect a significant improvement in image quality with SLSC imaging. Nevertheless, given the trends of increasing aperture size and higher number of array elements (in both dimensions), the hope is that the beamforming strategies presented in this dissertation will be highly relevant on the upcoming hardware, and that they will find a use in clinical practice.
Bibliography


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