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A Novel Approach to the Quantification of the Longitudinal Speed of Sound and its Potential for Tissue Characterization (Part - I)

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Abstract

This study presents a method to determine the longitudinal speed of sound in speckle-dominated ultrasound images. The method is based on the concept that the quality of an ultrasound image is maximized when the beamformer's speed of sound matches the speed in the medium. The method captures the quality of the ultrasound image using two, quantitative image-quality metrics: image brightness and sharpness around the intended focal zone. The proposed method requires no calibration, is computationally efficient, and is deployable on commercial ultrasound systems without hardware or software modifications. *Ex vivo* testing on tissue-mimicking phantoms indicates the method's accuracy in predicting the true speed of sound to within 1% of ground truth values.

Keywords

quantitative; speed; sound speed; longitudinal; ultrasound; beamformation; sharpness; brightness; FFT; PCA

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Introduction

Background and Motivation for Accurately Quantifying Longitudinal Speed of Sound

The speed of sound in normal human tissues varies significantly; it ranges from roughly 1430 m/s in breast tissue to 1647 m/s in muscle (Gyongy and Kollar 2015; Mamou and Oelze 2013). Despite this variation, clinical ultrasound scanners typically use an assumed speed of sound (1540 m/s) for image reconstruction. This assumption has several drawbacks. Since the assumed speed of sound determines the transmit and receive beamforming delay patterns, errors can lead to an aberration in the wavefront and acoustic beamshape and a shift in the location of the peak acoustic response (Anderson et al. 2000; Gyongy and Kollar 2015; Napolitano et al. 2006; Qu et al. 2012). A spatial shift of the intended focal zone, especially during receive beamforming, widens the associated point spread function (PSF) and changes the speckle characteristics in the ultrasound image (Anderson et al. 2000; Napolitano et al. 2006; Qu et al. 2012). Consequently, overall image quality is degraded due to an increase in lateral beam width, which reduces corresponding lateral resolution and ability to detect and resolve point targets and low contrast lesions (Anderson et al. 2000; Gyongy and Kollar 2015). The impact of speed of sound errors is exacerbated by use of low f-number transducers with higher transducer frequencies, i.e. at conditions corresponding to higher focusing strength. Accurate and robust speed of sound estimation will therefore help improve image quality.

A second and, perhaps more important, result of the ability to accurately and consistently predict the speed of sound *in vivo* lies in tissue characterization. The longitudinal speed of sound is often affected by tissue pathology (Bamber and Hill 1981; Gyongy and Kollar 2015; Imbault et al. 2017; Kumagai et al. 2014; Mamou and Oelze 2013; Qu et al. 2012). Consider, for example, the diagnosis of non-alcoholic fatty liver disease (NAFLD), which is characterized by diffuse infiltration of fat into the hepatocytes of the liver. Normal liver has approximately 5% fat content; this may increase to above 30% in advanced cases of steatosis. Fat has a relatively lower longitudinal speed of sound than healthy liver tissue. Consequently, the expected speed of sound in a fatty liver will be lower than that in a healthy liver (Bamber and Hill 1981; Ghoshal et al. 2012; Imbault et al. 2017; Kumagai et al. 2014). Experiments have demonstrated this speed reduction in *ex vivo* human liver samples; O'Brien et al. showed a speed of sound reduction of about 50 m/s in rats with liver lipid content ranging from a normal of 2-5% to slightly more than 20% (1988). There are other situations where fatty infiltration is associated with pathology. The use of speed of sound as a quantitative biomarker for fatty infiltration would likely be of value not only for diagnosis but also treatment monitoring.

Another relevant example is the use of ultrasound to determine bone quality (specifically bone density) in premature and full-term infants. Metabolic bone disease of prematurity (MBDP) is a common and significant problem that can give rise to fractures, osteomalacia, and osteoporosis (Teitelbaum et al. 2006). The standard of care for measuring bone density is dual energy X-ray absorptiometry (DEXA). However, quantitative ultrasound has emerged as a viable alternative; the longitudinal speed of sound and attenuation coefficient in bone correlates with bone density (Teitelbaum et al. 2006). In addition to being fast and

inexpensive, quantitative ultrasound has the benefit of not exposing infants to ionizing radiation and the potential to provide accurate and reliable diagnoses at point of care.

Speed of sound estimation is relevant in the field of breast imaging and early detection of breast cancer. Breast density, as assessed by mammograms, reflects breast tissue composition (Boyd et al. 2010). Breast has a relatively low longitudinal speed of sound (~1430 m/s) as it is primarily composed of fat. However, breast tumors have higher sound speeds and tend to cause increases in the bulk speed of sound (Boyd et al. 2010). Consequently, the ability to predict the longitudinal speed of sound *in vivo* is of importance in the longitudinal monitoring of breast health. Furthermore, knowledge of the speed of sound within the tumor and the surrounding breast tissue can greatly aid ultrasound image guided radiation treatment (IGRT), wherein an accurate speed of sound estimate can be used to better define and visualize the target (tumor or lesion).

In summary, the ability to accurately and consistently measure the longitudinal speed of sound *in vivo* has the potential to (1) improve the quality of ultrasound images and (2) to usher in novel diagnostic capabilities that leverage the low-cost, portability, and safety of quantitative ultrasound technology.

Existing Methodologies for Quantifying Longitudinal Speed of Sound

Estimating the speed of sound *in vivo* is a non-trivial task. Various methods have been proposed to estimate the longitudinal speed of sound *in vivo*; they have been classified into two categories by Robinson et al: transmission and pulse-echo (Qu et al. 2012). Transmission methods measure sound wave propagation time between a transmitter and a receiver, whereas pulse-echo methods estimate sound propagation speed by processing the associated backscattered data. Pulse-echo methods are further divided into three sub-categories: image aberration methods, intersecting beam transit-time methods and axial techniques (Qu et al. 2012). Among these are methods that use the best quadratic fit of the delay patterns applied to individual transducer elements, analyze the frequency domain of the B-mode image, adjust echo signals from several individual elements, or use blind deconvolution to estimate the speed of sound in speckle-dominated B-mode images (Qu et al. 2012). Other parameters commonly used in estimating sound speed include backscatter coefficients, speckle size, echo amplitude, and attenuation coefficients (Anderson et al. 2000; Chalasani et al. 2012; Ghoshal et al. 2012; Weijers et al. 2016). These methods exploit the idea that when the assumed speed of sound in the beamformer matches that in the tissue being examined, a resulting measure of the quality of the B-mode image is maximized. More specifically, in speckle-dominated B-mode images (e.g. those of the liver parenchyma), speckle brightness is maximized and speckle size is minimized when the true speed of sound is used by the beamformer during image formation (Nock et al. 1989).

The use of speckle to assess quality of beamformation arises from the work of Smith and Wagner (1983). They demonstrated, using speckle statistics, that speckle size is dependent on the use of an accurate speed of sound during beamformation, and that the smallest speckle dimensions occur near the focus. This concept was extended by Nock and Trahey who optimized speckle characteristics by adjusting beamformation delays until the brightness was the greatest at the desired focus (Nock et al. 1989).

Speed of sound estimation is closely allied to the more general topic of aberration correction. This is a topic that has received much attention by researchers with some success, however, to the authors' knowledge, no commercial instruments have incorporated these methods beyond an average speed of sound change.

Proposed Methodology

In this study, we quantify the bulk speed of sound by analyzing two B-mode image metrics: the sharpness in a region of interest (ROI) around the expected focal zone and the brightness of the image around the expected focal zone. The brightness of the image is obtained using a spatial average of the envelope of the corresponding in-phase/quadrature phase (IQ) data for a fixed band around the intended focal zone. The sharpness of the B-mode image is quantified using two different methods: i) the proportion of Fast-Fourier Transform coefficients above a defined threshold of the zero-frequency (i.e. DC) component of the image spectrum (De and Masilamani 2013) and ii) the singular values of spatial, intensity gradient of the image (Zhu and Milanfar 2009). These metrics are combined to yield a single, quantitative sharpness metric. It is worth noting that the sharpness and brightness metrics are very closely related to each other by Parseval's Theorem. An accurate estimation of the speed of sound within a medium allows for better focusing (transmit and receive) which in turn, leads to a sharper image and brighter speckle around the focal zone (the acoustic energy in the focal zone is maximized). As such, both metrics can be further combined into a single image quality metric. However, for the sake of rigorous analysis and discussions, the sharpness and brightness metrics have been decoupled.

The above metrics were selected for their ease of real-time implementation in low-cost systems, thereby offering a technique that can be performed on a conventional scanner at point of care such as the office of a primary care physician. These metrics can be extracted from radiofrequency (RF) data with minimal computational cost and no calibration (as required with back scatter coefficients), thus making them compatible with existing commercial ultrasound machines (Chalasani et al. 2012). An existing proof of the image sharpness method for the case of image quality optimization in a low-cost system exists in the work of Napolitano et al. (2006).

Materials and Methods

Explanation of Image Quality Metrics

The following three image-quality measures were used to estimate the speed of sound in speckle-dominated uncompressed B-mode images: 1) Image Brightness (Brightness), 2) Image Sharpness: Fast-Fourier Transform Coefficients (FFT), and 3) Image Sharpness: Principal Component Analysis (PCA).

Focal Zone Image Brightness (Brightness): For an assumed beamformation speed of sound, the intensity (or energy) envelopes of RF data are determined using the Hilbert Transform. The samples corresponding to a band around the expected focal zone (B_f) are extracted and a spatial mean is determined across all available A-lines (A). This results in an

estimate of the average brightness around the focal zone. The following equations summarize the metric:

$$M_B = \frac{1}{A} \left(\sum_A \left(\sum_{B_f} H(RF) \right) \right) \quad (1)$$

where H is the Hilbert Transform.

Image Sharpness: FFT Coefficients (FFT): Errors in the assumed beamforming speed of sound cause lateral blurring within the resulting B-mode image (Anderson et al. 2000; Wagner et al. 1983). In order to quantify the resulting blurring around the focal zone, the image sharpness metric proposed in (De and Masilamani 2013) is utilized:

$$M_F = \frac{Th}{M \times N} \quad (2)$$

where Th is the number of FFT coefficients whose magnitudes is greater than $\frac{DC}{1000}$ where DC is the magnitude of the zero-frequency component, and M and N are the dimensions of the image. The metric fundamentally extracts the effect of speed of sound mismatches and is easily applied to a B-mode image with no calibration and minimal processing. The region of interest (ROI) for this method is centered on the intended focal zone, but can vary with minimal effects on the accuracy. In addition to the count of FFT coefficients greater than a certain magnitude, an alternative based on the integration of Fourier coefficients above a given spatial frequency can be utilized. The goal is to get an estimate of the amount of energy that gets shifted from DC and very low spatial frequency values by improved focusing.

Image Sharpness: PCA Analysis (PCA): The metric proposed by Zhu et al. is utilized to quantify the magnitude of the intensity gradients within the B-mode image and thereby obtain a measure of the associated blurring (2009). The metric is summarized as follows (Zhu and Milanfar 2009):

$$M_P = \frac{S_1}{\epsilon} \quad (3)$$

where s_1 is the largest singular value corresponding to the matrix, G given by:

$$G = [I_x I_y] \quad (4)$$

where I_x and I_y are vectors corresponding to the directional gradients of intensity within the image, and ϵ is a small, arbitrary number (usually $5e^{-4}$) (Zhu and Milanfar 2009). The

largest singular vector corresponds to the direction along which the intensity gradient is the largest and the largest singular value captures the magnitude of this variation. It is noted that this metric requires only a region of interest (ROI) within the B-mode image and no additional calibration.

Combination of Image Sharpness Metrics: The two distinct image sharpness metrics detailed above were combined to yield a single sharpness metric:

$$M_S = (M_F)^{(1-r)}(M_P)^r \quad (5)$$

where r was chosen to be 0.25. The value was chosen optimally over the course of validating the proposed method.

It is worth noting that the presence of aberrating and occluding layers will affect the brightness and sharpness metrics, but will not preclude their use. Both metrics are relative metrics; hence, as long as the imaging configuration (inclusive of all occluding or aberrating layers) stays constant while the beamforming speed of sound is varied, the relative change in the metrics will still provide meaningful results. Also worth noting is that the sound speed predicted in these cases will be skewed by the presence of the occluding/aberrating layers. In other words, the metrics will still be applicable, but the predicted speed of sound will have to be corrected based on the depth of all occluding/aberrating layers preceding the domain of interest. This will be addressed in detail in the Part II of this manuscript titled “Experimental Validation of Longitudinal Speed of Sound Estimates in the Diagnosis of Hepatic Steatosis (Part II)” (submitted in parallel).

Simulations

A MATLAB-based, Fast Object-oriented C++ Ultrasound Simulation (FOCUS) was utilized to validate the proposed technique. FOCUS utilizes the fast near-field method to solve the non-linear, wave equation in three-dimensional space (McGough 2016) (MATLAB 2016b, MathWorks, Natick, MA, USA) (FOCUS 0.905, Michigan State, East Lansing, MI, USA). A tissue-mimicking domain was constructed with the following dimensions: 5 mm × 5 mm × 10 mm (x, y and z). A scatterer density of 80 scatterers/mm³ was used and point scatterers were randomly distributed within the bulk of the phantom. Scatterers were designed to have randomly distributed reflection coefficients. Simulations were conducted with a 256-element array with a radius of curvature equivalent to the focal depth. The element width was set to the effective wavelength of the transducer, the element height was set to 12 mm, the kerf was set to 50 microns and the number of active elements was set to 64. The sampling frequency was set to 75 MHz to eliminate aliasing effects and the axial and azimuthal focal depths were held constant at 5 mm (sound wave propagation was along the z direction).

In order to simulate the effect of uncertainty in the speed of sound, the true speed of sound within the computational domain was held fixed at 1500 m/s, 1550 m/s, and 1600 m/s (each simulated independently), while the assumed speed of sound for the beamforming process

was varied from 1480 m/s to 1620 m/s in increments of 10 m/s, and the transducer frequency was held constant at 7.5 MHz.

In order to demonstrate the invariance with respect to the transducer frequency, the transducer's center frequency was varied as follows: 5.5 MHz, 7.5 MHz, 9.5 MHz (each simulated independently) while the speed of sound in the medium was held fixed at 1550 m/s; once again, the assumed speed of sound for the beamforming process was swept from 1480 m/s to 1620 m/s in increments of 10 m/s. The outputs of the simulations were the resulting beamformed RF data and corresponding B-mode images.

The simulation domains used as part of this study did not contain any inhomogeneities in the form of inclusions or occluding layers with substantially different acoustic impedances. First, the issue of inclusions. The proposed metrics estimate the bulk speed of sound within the medium. Inclusions with speeds higher or lower than that of the medium would skew the prediction accordingly. The metrics would still produce a local maximum as a function of the beamforming speed and this predicted value would capture the presence of an inclusion. In order to disambiguate this value from the speed in the medium alone, the current technique would have to be augmented to allow for local speed of sound predictions. Second, the issue of occluding layers. Since the proposed metrics are relative, this technique would yield an estimate of the speed of sound with the medium of interest; however, the value would be skewed by the depth of the occluding/aberrating layer preceding the domain of interest. As mentioned before, this will be addressed in Part II of this manuscript titled "Experimental Validation of Longitudinal Speed of Sound Estimates in the Diagnosis of Hepatic Steatosis (Part II)" (submitted in parallel). Lastly, the scatterer density was held constant throughout the simulations; this value was chosen to mimic the density commonly found in human soft tissue. Wagnet et al. showed that ultrasound signals that result from a large number of uniformly distributed inhomogeneities is a random signal with values given by the Rayleigh probability density function (PDF), with an SNR of roughly 1.91 [Wagner et al. 1983]. This distribution was held fixed and constant throughout all simulations, because the scope of the paper is limited to speckle dominated, tissue mimicking media. Furthermore, the clinical application foremost in our minds is that of estimation of early stages of NAFLD, e.g. steatosis and steatohepatitis. Thus, we will be testing these methods on a large, fairly homogeneous organ, the liver. Further, steatosis and NASH are diffuse and non-focal diseases for the most part (this will, of course, be assessed during our clinical evaluations) so the impact of inclusions is unlikely. The clinical personnel will be instructed to avoid areas with large blood vessels and to try to use sites with minimal subcutaneous fat.

Experiments

The proposed method was tested in the following experimental configurations: i) Computerized Imaging Reference Systems Inc. (CIRS) Liver Phantom (true speed of sound = 1540 m/s) ii) CIRS Custom Phantom (true speed of sound = 1440 m/s); both phantoms were manufactured, tested and calibrated by CIRS (CIRS, Norfolk, Virginia, USA). The imaging of all specimens was performed on a General Electric (GE) Logiq E9 System with a 9 L probe at 9 MHz (GE, Boston, MA, USA). RF and B-mode images were collected from

the machine with differing assumed speeds of sound in the beamforming process ranging from 1400 to 1620 m/s in increments of 10 m/s.

Results

Simulations

Figure 1 shows the normalized image-quality metrics, brightness metric (M_B (Fig. 1A) and combined sharpness metric (M_S (Fig. 1B), as a function of the beamforming speed of sound for a transducer frequency of 7.5 MHz and true speeds of 1500 m/s, 1550 m/s and 1600 m/s within the medium. For both metrics, the predicted sound speed corresponds to a maximum normalized value of 1.0. The dashed lines represented the true speeds of sound within the medium: 1500 m/s (black), 1550 m/s (blue), 1600 m/s (red). Table 1 summarizes the results. As can be seen in Table 1, each of the metrics independently predicts the true speed of sound within the medium, thereby demonstrating the algorithm's invariance with respect to the true speed within the medium.

Figure 2 shows the normalized image-quality metrics, brightness (M_B (Fig. 2A) and sharpness (M_S (Fig. 2B), as a function of the beamforming speed of sound for transducer frequencies of 5.5 MHz, 7.5 MHz and 9.5 MHz, and a true speed of 1550 m/s within the medium. For both metrics, the predicted sound speed corresponds to a maximum normalized value of 1.0. The dashed green line represents the true speeds of sound within the medium i.e. 1550 m/s. Table 2 summarizes the results. As can be seen in Table 2, each of the metrics independently predicts the true speed of sound within the medium with minimal error, thereby demonstrating its invariance with respect to the transducer's center frequency.

Experiments

CIRS Liver Phantom: Figure 3 shows the normalized metrics as a function of the assumed beamforming speed of sound on the GE Logiq E9 for the CIRS liver phantom; both metrics (M_B and M_S) independently predicted the true speed of sound (1540 m/s) with no relative error. The relative errors were determined by comparing the predicted values to the ground truth value provided by CIRS (1540 m/s). The predicted speed of sound for each metric corresponds to a maximum, normalized value of 1.0. While there was no statistical difference between the estimation of each method ($p > 0.05$), the FFT method was found to be the most sensitive to speed of sound errors.

CIRS Custom Phantom: Figure 4 shows the normalized metrics as a function of the assumed beamforming speed of sound on the GE Logiq E9 for the CIRS custom phantom; the brightness metric predicted a speed of 1440 m/s (0.00% relative error) and the combined sharpness metric predicted a speed of 1440 m/s (0.00% relative error). The relative errors were determined by comparing the predicted values to the ground truth value provided by CIRS (1440 m/s). The predicted speed of sound for each metric corresponds to a maximum, normalized value of 1.0.

Conclusion/Discussion

Accurate and consistent determination of the longitudinal speed of sound *in vivo* has multiple advantages. It allows for the accurate creation of high-quality B-mode images while overcoming the pitfalls of decreased spatial resolution and inaccurate depth measurements. It also allows for the development of novel diagnostic tools that exploit the relationship between the longitudinal speed of sound and the pathology of the tissue under examination. The longitudinal speed of sound is an indicator of fat infiltration in the liver (hepatic steatosis). It also demonstrates a strong correlation with the bone densities of pre-mature and full-term infants. Quantitative ultrasound has emerged as a viable diagnostic tool in the early detection of breast cancer where the presence of potentially malignant tumors serves to skew estimates of the longitudinal speed of sound *in vivo*.

The proposed method involves the iterative estimation of the true speed of sound in speckle-dominated ultrasound images (similar to those of *in vivo* tissue) using two image quality metrics: image brightness (M_B around the expected focal zone and image sharpness around the expected focal zone (M_F and M_P as explained above). The method's capability to extract the true speed of sound was tested in simulation and tissue-mimicking phantoms. Comparison to ground truth measurements indicated the method's ability to predict the speed of sound to within 4.54% error without regard to the operating conditions (transducer frequency, medium under examination etc.) in a manner that necessitates minimal calibration and is readily adaptable to commercial ultrasound scanners. The proposed method, does however, have its share of drawbacks. The method is only capable of predicting the aggregate speed of sound within the medium; it cannot provide the requisite spatial resolution that would allow for the creation of a speed of sound map. A speed of sound map becomes especially important in the case of non-diffuse pathologies such as tumors in soft tissue or fibrosis in livers. The computational complexity associated with estimating the local speed of sound would also be considerably higher, necessitating access to and inversion of raw channel data (as opposed to beamformed RF data); this is under active investigation.

Moreover, the method assumes that the medium is in direct contact with the ultrasound transducer and no occluding layers are present. The presence of occluding layers (such as subcutaneous fat) will skew the speed of sound prediction. As such, while the proposed method is robust and quick, modifications to the method are necessary to demonstrate its feasibility in clinical settings. Another drawback is that because these metrics work best under low f-number configurations (where SOS errors are exacerbated), an accurate determination of the location of the focal zone within the image becomes important. This is particularly challenging in the presence of aberrating layers such as fat.

Concurrently, we are also studying some half a dozen different metrics for their robustness under various simulation tests. These will be discussed in future publications. We are already collaborating with MGH on setting up tests to evaluate these metrics initially at the animal level and eventually with a range of human patients. MGH is ideal for this evaluation since our collaborators have been very active participants in the QIBA study of shear wave speed

estimation of liver fibrosis and have developed excellent protocols for the associated experiments.

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Figure 1:

Predicted speed of sound in the simulation medium using the brightness metric (A) and combined sharpness metric (B). The transducer frequency was held fixed at 7.5 MHz while the true speed was varied as follows: 1500 m/s, 1550 m/s and 1600 m/s. The brightness metric predicted the following speeds: 1500 m/s, 1550 m/s and 1590 m/s, resulting in errors of 0.00%, 0.00% and 0.63%, respectively. The combined sharpness metric predicted the following speeds: 1490 m/s, 1550 m/s, 1600 m/s, resulting in errors of 0.67%, 0.00%, and 0.63%, respectively. The dashed lines correspond to the ground truth values; 1500 m/s (black), 1550 m/s (blue) and 1600 m/s (red).

Figure 2:

Predicted speed of sound in the simulation medium using the brightness metric (A) and combined sharpness metric (B). The true speed within the medium was held fixed at 1550 m/s while the transducer frequency was varied as follows: 5.5 MHz, 7.5 MHz, 9.5 MHz. The brightness metric predicted the following speeds: 1550 m/s, 1550 m/s and 1550 m/s, resulting in errors of 0.00% for each of the three frequencies. The combined sharpness metric predicted the following speeds: 1550 m/s, 1550 m/s, 1550 m/s, resulting in errors of 0.00%. The dashed green line corresponds to the ground truth value of 1550 m/s.

Figure 3:

Predicted speed of sound in the CIRS liver phantom; the predictions of both normalized metrics (brightness and combined sharpness) coincide with the calibrated value of 1540 m/s (dashed green line), resulting in a relative error of 0% for each of them.

Figure 4:

Predicted speed of sound in the CIRS custom phantom; both normalized metrics coincide (brightness and combined sharpness) to predict the speed of sound with minimal errors. The brightness metric predicts a speed of 1440 m/s (0.00% relative error) while the sharpness metric predicts a speed of 1440 m/s (0.00% error). The dashed green line represents the ground truth value of 1440 m/s.

Table 1:

Summary of algorithm validation for fixed center frequency (7.5 MHz) and varying true speeds of sound within the medium (1500 m/s, 1550 m/s and 1600 m/s)

Metric	True Speed of Sound (Frequency)	Predicted Speed of Sound	Percent Error
M_B	1500 m/s (7.5 MHz)	1500 m/s	0.00%
M_B	1550 m/s (7.5 MHz)	1550 m/s	0.00%
M_B	1600 m/s (7.5 MHz)	1590 m/s	0.63%
M_S	1500 m/s (7.5 MHz)	1490 m/s	0.67%
M_S	1550 m/s (7.5 MHz)	1500 m/s	0.00%
M_S	1600 m/s (7.5 MHz)	1590 m/s	0.63%

Table 2:

Summary of algorithm validation for a fixed speed of sound (1550 m/s) and varying transducer frequencies (5.5 MHz, 7.5 MHz, 9.5 MHz)

Metric	True Speed of Sound (Frequency)	Predicted Speed of Sound	Percent Error
M_B	1550 m/s (5.5 MHz)	1550 m/s	0.00%
M_B	1550 m/s (7.5 MHz)	1550 m/s	0.00%
M_B	1550 m/s (9.5 MHz)	1550 m/s	0.00%
M_S	1550 m/s (5.5 MHz)	1550 m/s	0.00%
M_S	1550 m/s (7.5 MHz)	1550 m/s	0.00%
M_S	1550 m/s (9.5 MHz)	1500 m/s	0.00%