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The Impact of Physiological Motion on Tissue Tracking During Radiation Force Imaging

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Abstract

The effect of physiological motion on the quality of radiation force elasticity images has been investigated. Experimental studies and simulated images were used to investigate the impact of motion effects on image quality metrics over a range of clinically realistic velocity and acceleration magnitudes. Evaluation criteria included motion filter effectiveness, image signal-to-noise ratio (SNR), and the contrast-to-noise ratio (CNR) of a stiff inclusion embedded in a homogeneous background material. Two transmit frequencies (2.5 and 4.4 MHz) were analyzed and contrasted in terms of image quality over a range of target motions. Results indicate that situations may exist where liver and cardiac motion magnitudes lead to poor image quality, but optimized transducer orientations may help suppress motion artifacts if some *a priori* information concerning target motion characteristics is known. In the presence of significant target motion, utilizing a lower transmit frequency can improve SNR and CNR in elasticity images.

Keywords

Ultrasound; Ultrasonic Imaging; Acoustic Radiation Force; Abdominal Imaging; Elastography; Physiological Motion

Introduction

Methods of imaging tissue elasticity have been investigated by many groups in recent years. A summary of much of this research and a collection of relevant literature is provided in a review by Greenleaf et al. (2003). The various elasticity imaging techniques may differ in implementation and/or strategy, but share a common goal of detecting potential disease through the remote interrogation of tissue mechanical properties. Tissue stiffness is often related to pathology (Anderson and Kissane, 1953; Ophir et al., 1991; Yeh et al., 2002; Sandrin et al., 2003), and elasticity imaging methods hold diagnostic promise as a supplement to more conventional imaging techniques. Elasticity imaging methods are also currently being investigated for guidance of interventional procedures (Righetti et al., 1999; Varghese et al., 2002; Konofagou and Hynynen, 2003; Curiel et al., 2005; Fahey et al., 2005b, 2006; Hsu et al., in press) and other applications (see, for example, Langevin et al. (2004)).

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The bulk of the ultrasound-based elasticity imaging techniques rely on cross-correlation algorithms (Trahey et al., 1987; O'Donnell et al., 1994) to estimate tissue motion from sequentially-acquired lines of radiofrequency (RF) data. Although higher-dimensional algorithms are generally associated with improved performance (Insana and Hall, 1998; Konofagou and Ophir, 1998; Geiman et al., 2000), computational overhead often restricts speckle tracking to the dimension of beam propagation in applications requiring rapid image visualization (Pinton et al., 2006). These tracking algorithms use knowledge of the RF sampling frequency to calculate the time delay between a selected region in one RF line and the location of the correlation function peak from within a search region in a second RF line. This time delay is subsequently converted into a displacement by assuming a speed of sound.

The performance of correlation-based RF time delay estimators has been studied both theoretically and experimentally (Walker and Trahey, 1995; Cespedes et al., 1997; Pinton et al., 2006). The Cramér-Rao lower bound (CRLB) describes a fundamental limit on the performance of an unbiased time delay estimator for partially-correlated RF signals (Walker and Trahey, 1995). Although the minimum displacement estimate variance predicted by the CRLB may be small, in the presence of increased speckle pattern decorrelation the magnitude of displacement estimate errors (jitter) will rise (Walker and Trahey, 1995; Cespedes et al., 1997). In elastography, this decorrelation between pre- and post-compression RF data may be significant if large strain fields are introduced. Radiation force elasticity imaging methods generally utilize small ($< 40 \mu\text{m}$) displacements (Nightingale et al., 2002; Bercoff et al., 2004; Melodelima et al., 2006), and decorrelation effects are typically subtle and mostly attributable to shearing occurring under the tissue tracking point-spread function (PSF) (McAleavey et al., 2003). In acoustic radiation force impulse (ARFI) imaging, under typical abdominal imaging conditions the root-mean-square (RMS) magnitude of jitter errors is on the order of $0.2 \mu\text{m}$ (Palmeri et al., 2006). However, as radiation force-induced displacements in tissues are small, even marginal increases in jitter magnitude may significantly impact image signal-to-noise ratio (SNR).

Many tissues, such as blood vessels, the liver, and the heart, experience non-negligible tissue motions arising from physiological events. Previous efforts have investigated the feasibility of using these physiological motions as the primary stimuli for elasticity imaging (D'hooge et al., 2002; Varghese and Shi, 2004), but in many applications this motion is considered a noise source which may significantly decorrelate pre- and post-stimulus RF lines. This decorrelation increases the magnitude of jitter errors and lowers image SNR. Further complications are associated with distinguishing physiological-based tissue displacements from those induced via external stimuli (such as controlled compression or radiation force). Motion patterns for a given region of tissue may not be cyclic on a sub-millimeter scale, and tissue velocity and acceleration profiles may vary considerably within different regions of the same organ (Kolen et al., 2004). Consequently, methods of predicting, controlling, and compensating for physiological motion have been proposed and evaluated by several groups (Kolen et al., 2004; Shi et al., 2005; Chandrasekhar et al., 2006).

Motion effects will be manifested differently in radiation force elasticity images relative to images acquired with compressional elastography techniques. Radiation force displacements may be more than two orders of magnitude smaller than those encountered in elastography, and thus higher correlation values between RF data lines are necessary in order to maintain reasonably low jitter magnitude and adequate image SNR. Also, in many techniques (including ARFI imaging), one region of tissue (*i.e.* one image line or set of image lines (Dahl et al., in review)) is interrogated in its entirety before data from a new region is collected. Since the total sampling time (generally less than 5 ms) for each region is shorter than in most elastography applications (Chandrasekhar et al., 2006), tissues may be required to be stable for shorter periods of time. Additionally, assumptions concerning the profiles of tissue

displacements attributed solely to physiological motion are likely more valid when applied over shorter monitoring windows.

The aim of the current study is to evaluate the impact of physiological motion on ARFI image quality. Although we will focus on ARFI imaging methods, the analysis extends to other radiation force elasticity imaging methods that track tissue displacements as well. Previous work has indicated that during *in vivo* abdominal scanning, ECG-triggering used in conjunction with patient breath-hold helps avoid most extreme gross physiological motions, and thus allows for quality ARFI images to be acquired in many regions (Fahey et al., 2005a). However, knowledge of motion-related limitations will likely increase the rate of imaging success in highly mobile regions (such as in liver tissues neighboring major blood vessels or close to the heart). We employ the use of a simulated liver tissue model to assess the ability to make quality ARFI images at a clinically realistic range of tissue velocities and accelerations. Specifically, we evaluate the ability to identify and remove physiological motion from tracked tissue displacements in order to recover the radiation force-induced displacement profile. We also analyze the normalized correlation coefficients obtained from tracking lines of RF data in the presence of target motion and the corresponding impact on image jitter and SNR. For comparative purposes, two transmit frequencies (2.5 and 4.4 MHz) are investigated and analyzed in terms of the detectability of a stiff inclusion.

Background

Physiological tissue motion affects the quality of ARFI images through two major mechanisms: (1) Artifacts in tracked displacements that are unrelated to incident radiation forces and, (2) Increased image jitter resulting from motion-induced decorrelation between RF lines used for tissue tracking. Although the impact of these mechanisms on image quality are related, it is more intuitive to first consider them separately. Following this discussion of motion effects, a brief introduction of ARFI imaging with a curvilinear scanning geometry and an overview of the coordinate terminology utilized in this document are presented.

Displacement Artifacts and Motion Filtering

Physiological tissue motions may be large relative to those induced *via* incident radiation forces. Additionally, these tissue motions may not be uniform within the image field-of-view (FOV), and the associated displacements are not necessarily reflective of underlying tissue mechanical properties. Further displacement artifacts will be introduced if the position of the transducer relative to the target tissue does not remain stable during data acquisition. In order to construct an image related to tissue elasticity, these displacement artifacts need to be identified and removed. Therefore, ARFI imaging in the presence of unwanted tissue/transducer motion becomes a two-step process. First, it is necessary to track all relative tissue/transducer displacements as accurately as possible. Subsequently, we try to remove displacements not related to applied radiation forces by making assumptions pertaining to their expected temporal behavior.

Although higher-order and more sophisticated motion filters are currently under investigation, analysis in this study is limited to the linear motion filter that has been previously implemented (Nightingale et al., 2002). This filter is used to compensate for motion artifacts that occur in the tracking dimension. Components of physiological motion in other dimensions do not produce motion artifacts, but may decorrelate RF lines used for tracking (see below). The filter algorithm is designed based upon the assumption that over the very short (< 5 ms) time window where a region of tissue is being monitored, any transducer and/or physiological motion can be approximated with a linear temporal profile (i.e., no acceleration). The validity of this approximation is questionable in many instances, but the filter may still perform adequately in the presence of mild velocity fluctuations.

Figure 1 illustrates the functionality of the linear motion filter. In (a) and (b), in addition to radiation force-induced displacements, we have introduced a constant velocity (4 mm/s) motion of the target away from the transducer. The displacement estimate produced by the tracking algorithm is shown in (a). In this case, the small ($< 4 \mu\text{m}$) ARFI displacements are partially obscured by the larger displacements associated with bulk target motion.

To remove the physiological motion from the initial displacement estimate, we choose a cutoff time, t_{cut} , when we believe the tissue will have completely recovered from the radiation force excitation. The values of t_{cut} are chosen based upon our experience of tissue displacement temporal profiles and Finite Element Method (FEM) models detailing the response of soft tissue to impulsive radiation force (Palmeri et al., 2005), and will differ based upon factors such as expected tissue elastic modulus. To begin, a line is fit between the origin (zero displacement and zero elapsed time) and the tracked displacement at time $t = t_{cut}$ (see Fig. 1 (a)). This linear temporal displacement profile is then subtracted from the original displacement estimate. If successful, the displacement profile attributable solely to applied radiation force is recovered, as in Fig. 1(b). This process is repeated for each displacement estimate (pixel) in the image. The velocity estimate for a pixel is determined by averaging the estimated velocities of the pixel in question and those from a number of pixels surrounding it radially, with a typical averaging window length being 3 pixels.

Figure 1(c) illustrates motion filter performance when the design assumptions do not hold true. In this case, in addition to radiation force displacements, we have introduced a constant acceleration (5 mm/s^2) motion of the target away from the transducer. The original tracked displacement estimate and the output of the linear motion filter when the same value of t_{cut} is chosen as in Fig. 1(b) are shown. In this example, the motion filter does not perform adequately and the output displacement profile is severely distorted relative to the ideal recovered profile shown in (b). Note that in the first few ms of the tracking period, the sign of the motion filter error relative to the true displacement is opposite to the direction of the acceleration.

Jitter-related Limitations

The CRLB places a fundamental limit on the accuracy of an unbiased time-delay estimator operating on partially-correlated RF signals in the presence of noise. An analytical expression for the CRLB in this application has been derived by Walker and Trahey (1995):

$$\sigma \geq \sqrt{\frac{3}{2 f_c^3 \pi^2 T (B^3 + 12B)}} \left[\frac{1}{\rho^2} \left(1 + \frac{1}{\text{SNR}^2} \right)^2 - 1 \right], \quad (1)$$

where σ represents the standard deviation of jitter errors, f_c is the transducer center frequency, T is the kernel length, B is the bandwidth of the transducer, and ρ is the normalized cross-correlation coefficient. In many situations, mean jitter values are very close to zero, and thus σ is typically representative of jitter magnitude. Experimentally achievable jitter levels in ARFI imaging may be smaller than theoretically predicted by the CRLB, in part due to the fact that the estimators are biased (Pinton et al., 2006). As mentioned previously, under typical ARFI imaging conditions, jitter magnitude may be as small $0.2 - 1 \mu\text{m}$. SNR in ARFI images is thus typically on the order of 15 - 30 dB.

When imaging organs with significant physiological motion, ARFI image SNR may decrease significantly. The speckle patterns used to track tissue displacement have limited spatial coherence, particularly in the lateral and elevation (out-of-plane) dimensions (Wagner et al., 1983; Ramamurthy and Trahey, 1991). If 1D tracking is utilized, even small (fractions of a beamwidth) shifts of the target region in these transverse dimensions will lower the correlation coefficient between a reference kernel of RF data and its displaced companion in a second RF line. As implied by Eq. 1, these lower correlation values lead directly to higher minimum jitter

levels. Lower correlation coefficients between true pattern matches may also lead to errors due to false peaks, although these errors are less troublesome because they can generally be identified and removed with non-linear processing methods. Jitter errors, however, cannot be removed (Walker and Trahey, 1995), and thus affect SNR and overall image quality.

In the presence of tissue motion, jitter errors play an additional role in decreasing ARFI image SNR. The linear motion filter traditionally used is a pixel-by-pixel algorithm. However, jitter errors from each displacement estimate are uncorrelated and the magnitude of deviation from the true displacement may fluctuate from pixel to pixel. Thus, the motion filter algorithm will estimate a different amount of physiological/transducer motion at each point, even in the presence of a uniform target velocity. Averaging of estimated velocities over a number (for example, 3) of pixels helps counter this discrepancy, but minor differences in motion filter aggressiveness will persist. This adds an additional displacement variance to the data displayed in the motion-filtered ARFI image. The significance of this second source of displacement variance increases as the correlation between speckle patterns used for tracking decreases.

Curvilinear Geometry

Both experimental and simulated data were collected using a curvilinear scanning geometry. This geometry was chosen because it is appropriate for abdominal scanning in most cases. ARFI imaging with this geometry is very similar to imaging with a linear geometry, but slight differences exist. Per usual, displacements are estimated in the direction of beam propagation. However, because of the angular orientation of the tracking beams, it is radial (as opposed to axial) displacements that are tracked.

The consequence of the curvilinear geometry is that a lateral target motion (perpendicular to the tracking beam oriented at an angle of 0° - see Fig. 2) will produce motion artifacts with radial components, with the magnitude of the radial component increasing with increasing angle magnitude. The motion artifacts induced will also differ in sign (positive vs. negative) on each half of the image. In the presence of lateral target motion, the amount of radial displacement measured by a tracking beam θ degrees from the central axis can be described by:

$$U_{radial} = U_{lateral} * \sin \theta, \quad (2)$$

where U_{radial} and $U_{lateral}$ describe the radial and lateral components of the displacement, respectively. Similarly, purely axial target translations will have motion components in the theta direction for beams off the central axis. Since we are generally not tracking displacements in this dimension, these movements will lead to speckle pattern decorrelation but not create a significant motion artifact.

Methods

Experimental Measurements

Experiments were performed with the use of a uniform tissue-mimicking phantom (CIRS Corporation, Norfolk, VA) having mechanical and acoustic properties (elastic modulus of 4 kPa, attenuation of 0.75 dB/cm/MHz) similar to those associated with liver tissue. Experimental phantom data were acquired using a Siemens SONOLINE Antares™ scanner (Siemens Medical Solutions USA, Ultrasound Division, Issaquah, WA) that has been modified to allow for custom beam sequencing and access to raw RF data. A Siemens CH6-2 transducer operating at 2.5 MHz and focused at a depth of 6.5 cm was used to collect data. ARFI pushing beams (*i.e.*, radiation force pulses) were unapodized and transmitted with an aperture size corresponding to an f-number of 3.5 (F/3.5). Pushing beams had a pulse length of 280 μ s. Tracking beams were standard B-mode imaging pulses transmitted with an F/3 aperture and a

pulse repetition frequency of 4300 Hz. A cross-correlation algorithm (kernel size of 0.9 mm) was used to track displacements in the radial dimension (Pinton et al., 2006). The reader is referred to prior publications for further elaboration on ARFI imaging beam sequencing and acquisition techniques (Nightingale et al., 2002; Fahey et al., 2005a).

During data acquisition, bulk physiological motion was mimicked using a Newport model MM3000 linear translation stage (Newport Corporation, Irvine, CA) to move the transducer with controlled velocity and acceleration profiles. To assess the effect of motion in a particular dimension on image quality, the transducer was moved along each orthogonal axis individually as well as in all three dimensions simultaneously. The translation stage utilized had maximum achievable velocity and acceleration magnitudes of 5 mm/s and 25 mm/s² on each axis (maximum vector magnitudes of 8.66 mm/s and 42.5 mm/s² with all three axes moving simultaneously). Simulations (described below) were used to extend analysis to larger magnitude velocities and accelerations.

For each target velocity/acceleration, 10 data sets were acquired, each with a different initial position in the phantom. For each data set, average values of the magnitude of the motion-induced displacement artifact (the amount of tracked displacement minus the known radiation force displacement from the stationary imaging case), normalized correlation coefficient, and RMS jitter magnitude were calculated in a region of interest (depths of 4 - 6 cm) where image quality is generally high and the strength of applied radiation force is fairly uniform. Statistical calculations were made using displacements tracked 0.9 ms following the cessation of radiation force. Values from all 10 data sets were then averaged, with data points lying more than 2 standard deviations from the mean considered statistical outliers and removed prior to analysis.

Physiological Motion Simulations

Simulated images of a uniform tissue-mimicking phantom were used to evaluate the impact of physiological motion on ARFI image quality over a greater range of velocities and accelerations than were available experimentally. Simulated phantoms were created by populating a 8.9 cm × 5 cm × 1 cm region with identical randomly-placed point scatterers. The number of point scatterers was determined by evaluating simulated B-mode image SNR over a range of populations (Wagner et al., 1983; Palmeri et al., 2006). This method yielded a scatterer density of approximately 11 scatterers per -6 dB resolution volume and total scatterer counts of 118,584 (2.5 MHz runs) and 740,532 (4.4 MHz runs). The simulated phantoms were assigned acoustic and mechanical properties matching those of the experimental test phantom (described above).

Simulated ARFI images were created using a multi-step approach. The FIELD II ultrasound simulation package (Jensen and Svendsen, 1992) was used to create synthetic RF data representative of a diffuse scattering phantom. In each spatial location, a reference line of RF data was first created of the phantom in its initial state. Scatterers were then displaced from their reference positions based upon the response of the simulated phantom to applied radiation forces. This response was characterized using FEM models in a manner described in detail previously (Palmeri et al., 2005, 2006). The amplitude of the peak focal displacement ($\sim 3 \mu\text{m}$) was chosen to correspond with displacement amplitudes induced experimentally in the phantom study described above. FIELD II was then used to create additional lines of RF data spaced by 0.23 ms (the experimental pulse repetition interval) to capture the temporal characteristics of the radiation force-induced displacements in the simulated phantom. To simulate electronic noise present in experimental measurements, uniformly-distributed random variations were added to simulated RF data. The simulated tracking and pushing beams were modeled with the experimental beam parameters specified above.

In addition to simulated radiation force displacements, phantom scatterers were also displaced from their reference positions in a manner representative of bulk physiological motion. For constant velocity simulations, phantoms were given bulk velocities ranging from 0.1 - 20 cm/s. As in the experimental data, both uni-axial and multi-axis motions were simulated. The effect of target acceleration was also investigated. Phantoms were given bulk accelerations ranging from 20 - 1732 cm/s² in both uni- and multi-axis motion formats. Initial velocities in simulations with target acceleration ranged from 0 - 2 cm/s in the dimension(s) of acceleration. All bulk target motions were in the positive coordinate directions relative to the axes in Fig 2. As a first step, all simulations accounted only for bulk motion, and neglected effects related to motion-induced target shearing, compression, or rotation. Commentary on the consequences of this approximation will be provided later in the *Discussion* section of this document.

Two transmit frequencies (2.5 and 4.4 MHz) were simulated in order to conduct an initial investigation into the effect of transmit frequency on image quality in the presence of motion. In both cases, the transmit frequency used was simulated as being the center frequency of the transducer. All other imaging parameters (f-number, focal depth, etc.) were identical for both frequencies. For a subset of target velocities, a stiff (16 kPa) cylindrical inclusion with a 1 cm radius was placed in the center of the simulated phantom so that boundary definition and contrast-to-noise ratio (CNR) could be included as criteria when evaluating overall image quality. CNR was determined using the following formula:

$$CNR = \frac{\bar{U}_b - \bar{U}_i}{\sqrt{\sigma_b^2 + \sigma_i^2}}, \quad (3)$$

where $\bar{U}_b$ is the mean displacement estimate of a region of phantom background material, $\bar{U}_i$ is the mean displacement estimate in a region of the inclusion, and σ_b^2 and σ_i^2 represent the variances of the displacement estimates in the same background and inclusion regions, respectively.

For each transmit frequency, simulations were run for 10 different simulated phantoms, each with different initial scatterer positions. For each phantom, average values of the motion artifact magnitude, correlation coefficient, and RMS jitter magnitude were calculated over the same range of depths examined experimentally. Values from all 10 phantoms were then averaged, with data points lying more than 2 standard deviations from the mean considered statistical outliers and removed prior to analysis. Unless otherwise specified, results shown correspond to displacements tracked 0.9 ms following the removal of radiation force, a time typically associated with peak focal displacement in abdominal applications.

Models were validated by comparing simulated 2.5 MHz data with experimental measurements. Qualitative comparisons were made by comparing patterns of tracked displacement in pre-motion filtered images. Quantitative validation was accomplished through comparison of statistical quantities over the velocity range achievable by the translation stage used in the experimental setup.

Results

Model Validation

Figure 3 illustrates two examples of the qualitative comparisons used in the model validation process. (a) and (b) show normalized experimental and simulated ARFI images, respectively, of a stationary phantom target. These are the control images that are used as references for calculations of the magnitude of the motion-induced displacement artifact. (c) and (d) show normalized experimental and simulated ARFI images acquired in the presence of a 5 mm/s

lateral target velocity. Each image in Fig. 3 is presented with a restricted FOV in order to enlarge regions of interest. No motion filtering has been performed.

In both examples, qualitative comparisons indicate that the simulated ARFI images depict behavior that is representative of that exhibited in the experimental images. In the stationary images, the radial locations of maximum tracked displacement (~ 4.5 cm) match well, and the variations in tracked displacement with depth are comparable. Note that the depth of maximum tracked displacement is located proximal to the focal depth, consistent with previous experiments that utilized deeply-focused radiation forces to induce displacements in absorbing media (Fahey and Trahey, 2004; Fahey et al., 2006). Similar agreement is exhibited by the lateral motion images shown in Figs. 3(c) and (d). It is noteworthy that the target motion induces a positive displacement artifact in scan lines on the right side of the image, while scan lines on the left side of the image experience minimal overall displacement due to the competing natures of the displacement artifact and the radiation force displacements.

Experimental and simulated ARFI images were also found to be very similar from a quantitative perspective. Data comparing the magnitude of the motion-induced displacement artifact, the average cross-correlation coefficient, and the average magnitude of jitter errors indicated agreement between the model and the experimental data over the full range of target velocities achievable experimentally. This agreement existed both for uni-axial and multi-axis target motions. In the overwhelming majority of cases, error bars (representing ± 1 standard deviation from the mean) overlapped for data points representing simulated and experimental data. For brevity, figures illustrating quantitative model validation results are not included in this document.

Motion Filter Effectiveness

The linear motion filter utilized in this study assumes that any target motion not associated with applied radiation forces will be of constant velocity. Both simulation and experimental results indicate that when this criteria holds true, the linear motion filter does an exceptional job of removing transducer/physiological motion from displacement estimates. The only difference between images of stationary phantoms and motion-filtered images of targets moving with a constant velocity is the aforementioned minor increase in the displacement estimate variance in the post-filtered images (see the *Background* section of this document). Due to space considerations, images illustrating motion filter effectiveness for constant velocity motions are omitted here, and instead we will focus on determining acceleration magnitudes that, when present, will degrade motion filter performance to the point where image quality suffers significantly. An example of motion filter effectiveness in the presence of constant velocity motion is provided in Table 1. Additionally, examples of motion-filtered images of targets undergoing constant velocity bulk displacements are shown in a different context later in this section, in Fig. 8.

Figure 4 provides a qualitative comparison of motion filter performance when uni-axial target accelerations are present along each orthogonal axis. (a) and (d) show images of a simulated phantom with axial accelerations of 10 and 40 cm/s^2 , respectively. (b) and (e) show images with acceleration magnitudes of 100 and 300 cm/s^2 in the lateral dimension, while (c) and (f) show images with acceleration magnitudes of 100 and 300 cm/s^2 in the elevation dimension. In each case, the phantom was initially stationary and did not undergo any bulk acceleration until the termination of radiation force application. The ideal recovered image is that of a stationary simulated phantom, as shown in Fig. 3(b). The outlined region in (a) is associated with the quantitative analysis provided in Table 1. All images were created with a motion filter cutoff time of 6.5 ms (typical for abdominal applications).

It is evident from Fig. 4 that axial accelerations have the most significant impact on motion filter performance. This stems from the fact that axial accelerations have large radial components, and the algorithm is attempting to estimate a constant radial velocity. For the 10 cm/s² axial acceleration shown in (a), the motion filter algorithm has suppressed a portion of the radiation force displacement magnitude by overestimating the mean target velocity, despite a total bulk velocity change of only 0.047 cm/s over the tracking interval. This effect is amplified in (d), where the axial acceleration was 40 cm/s² and the total bulk velocity change over the tracking interval was 0.19 cm/s.

Lateral accelerations also impact motion filter performance, as evidenced by Figs. 4(b) and (e). However, the motion filter algorithm is relatively more tolerant of lateral velocity fluctuations, which have smaller radial components. Lateral acceleration magnitudes on the order of 100 cm/s² begin to impact the effectiveness of the motion filter. The image in (e) indicates that further increases in lateral acceleration magnitude will result in motion-filtered images that are not reflective of actual radiation force displacements (*i.e.*, non-uniform displacement field in uniform media). Inspection of the images shown in (c) and (f) indicate that the motion filter is very tolerant of accelerations in the elevation dimension, since these accelerations have no radial component. These images do, however, appear to be more noisy than the reference case in Fig. 3(b), likely due to decorrelation/jitter effects related to target motion.

A quantitative analysis of motion filter performance in the presence of target acceleration is presented in Table 1. Three acceleration magnitudes are shown for each motion axis, as well as the percent error associated with each filtered displacement estimate relative the reference case in Fig. 3(b). Also shown are results from a zero acceleration case, where the target was undergoing a three-axis motion with a constant vector velocity of 0.87 cm/s (0.5 cm/s along each principle axis). Percent errors were computed in the outlined region of Fig. 4(a). The negative errors associated with axial acceleration represent an underestimation of the true radiation force displacement, and results from increases in velocity away from the imaging transducer.

The results shown in Fig. 4 and Table 1 are for simulated phantom targets that are initially stationary. Figure 5 investigates the effect an initial velocity would have on filter performance. (a) shows a motion-filtered image of a simulated phantom with an initial axial velocity of 2 cm/s and an axial acceleration of 10 cm/s², (b) shows a motion-filtered image of a simulated phantom with an initial lateral velocity of 2 cm/s and a lateral acceleration of 100 cm/s². Comparison of these images to their counterparts in Fig. 4 indicates that the initial velocity has minimal impact on the performance of the motion filter, and any degradations in image quality associated with the initial velocity are related to motion-induced decorrelation/jitter effects. Differences in the percent error associated with the filtered displacement estimates of images with the two initial conditions are less than 2%.

Correlation and Jitter Analysis: 2.5 MHz

Figure 6 shows simulation results for the full range of uni-axial target velocities investigated for a transmit frequency of 2.5 MHz. In the focal zone, effects stemming from multi-axis target motions can generally be described as a superposition of the effects associated with each single axis motion component, and are not shown. Figure 6(a) shows results for the normalized correlation coefficients, and (b) shows results for the magnitude of jitter errors. Results shown are for a scan line near the left side of the image (-12°), where motion artifacts can be large (see Figs. 3 and 4). All statistics were tabulated prior to motion filtering. Error bars represent ± 1 standard deviation from the mean.

The normalized correlation coefficients of the tracked data are shown in (a). The majority of target displacements induced by axial motion are along the radial axis of the scan lines in the image (see Fig. 2). Thus, correlation values remain high with this target motion, due to both the stability of the system PSF in the radial dimension and the fact that this is the tracking dimension. Correlation values decrease more quickly with motion in the lateral and elevation dimensions. The severity of decorrelation in these dimensions is related to the beamwidth of the tracking beams (Wagner et al., 1983), and thus may vary considerably with depth in a focused system. Lateral beamwidths are generally tighter than elevation beamwidths, and thus RF lines decorrelate more rapidly with lateral target translations.

The plots of RF line correlation in (a) correspond directly to the plots of the magnitude of jitter errors shown in (b). Although jitter magnitude remains relatively small in the presence of axial target motion, transverse motions cause jitter magnitude to rise to levels that will significantly impact image quality. For a target velocity of 10 cm/s, jitter magnitude is $1.2\text{ }\mu\text{m}$ for elevation motion and $3.1\text{ }\mu\text{m}$ for lateral motion. It should be noted that these jitter levels are specified for a tissue region with approximately $3\text{ }\mu\text{m}$ of radiation force displacement. Larger radiation force-induced displacements create larger shearing gradients under the tracking PSF, and generally also lead to increased jitter magnitude (Palmeri et al., 2006). Thus, although jitter magnitude remains pertinent information, it alone may not be the ideal indicator of image quality.

A better metric for evaluating overall image quality may be SNR, where for the current analysis we will define the ‘signal’ to be the average displacement estimate in a homogeneous region and the ‘noise’ to be the RMS jitter magnitude in that same region. Table 2 provides SNR values (determined in the region boxed-off in Fig. 3(b)) for the stationary reference image, images with uni-axial velocities of 5 and 10 cm/s along each axis, and an image with a multi-axis velocity of 8.7 cm/s (5 cm/s simultaneous motion on each axis). All calculations were performed after the motion filter had been applied to tracked displacement data. As shown, image SNR is impacted rather dramatically by lateral target motions. For perspective on how image SNR is related ARFI image quality, one can inspect the background regions of the simulated phantom images shown in Fig. 8.

It is important to remember that the image quality metrics described in this paper are time dependent, and that the results shown in Fig. 6 and Table 2 are specific to displacements tracked at a particular time (0.9 ms) after radiation force application. Figure 7 shows how ARFI image SNR varies with displacements tracked at different times following radiation force application. Shown are results for a stationary phantom, a phantom with a 5 cm/s lateral velocity, and a phantom with a 10 cm/s elevation velocity. All times are relative to the end of the radiation force pulse. SNR values were calculated in the enclosed region shown in Fig. 3(b).

In the stationary phantom, ARFI image SNR reaches a value near 14 dB at a time of 0.9 ms (the time of maximum focal displacement), and remains relatively high for later tracking times. In stationary targets, the magnitude of jitter errors is related to shearing under the tracking beam PSF, which decreases with time. Thus, even though tissues are recovering and displacement magnitude decreases with time, image SNR remains relatively constant due to a simultaneous decrease in jitter magnitude. For non-stationary targets, motion-induced decorrelation effects cause jitter magnitude to increase as the acquisition delay between reference and tracking RF lines increases. ARFI image SNR peaks at the time of maximum focal displacement, then decreases as the time when the displacement estimate is made is increased.

Impact of Transmit Frequency

According to Eq. 1, an increase in transmit frequency should result in a decrease in the magnitude of jitter errors. Higher transmit frequencies are also associated with improved image resolution. As a result of this decreased resolution volume, RF lines used for tracking tissue displacements will decorrelate faster with target motion when transmit frequency is increased. This section analyzes these competing effects with regard to image quality and the detectability of a stiff inclusion.

Table 3 compares the mean jitter magnitude of 10 simulated trials for transmit frequencies of 2.5 and 4.4 MHz. In addition to the stationary reference case, results are shown for target velocities of 5 cm/s along each orthogonal axis. Results are for a scan line on the left side of the image (-12°). In agreement with Eq. 1, the higher transmit frequency simulation produced images with lower jitter magnitude when the target was stationary. However, in the presence of target motion, the decorrelation of the RF lines used for tracking dominates any jitter improvement gained from increasing the transmit frequency, and jitter levels are higher for the 4.4 MHz images.

In order to evaluate the impact of the data provided in Table 3 on image quality, we created simulated ARFI images of an inclusion phantom moving with a range of uni-axial velocities for both transmit frequencies. These data are shown in Fig. 8. The top row shows images with a transmit frequency of 2.5 MHz, the bottom row shows images with a transmit frequency of 4.4 MHz. Shown from left to right are images acquired in the presence of (a and e) no bulk target motion, (b and f) 10 cm/s axial target velocity, (c and g) 10 cm/s elevation target velocity, and (d and h) 5 cm/s lateral target velocity. Motion filtering has been performed on all images to remove displacement artifacts. All images have been normalized and are shown with the same displacement scale.

Table 4 serves as a quantitative companion to Fig. 8, and shows CNR values for each image (as well as CNR values for target velocities not shown in the figure). The inclusion and phantom background regions used to determine CNR (see Eq. 3) are indicated by the white and black boxes, respectively, in Fig. 8(a). All CNR values were calculated after motion filtering was performed, and thus the displacement variances include contributions both from jitter errors and from pixel-to-pixel variations in motion filter performance.

From both a qualitative and a quantitative perspective, the 4.4 MHz image of the stationary phantom (e) is the best quality image of those shown in Fig. 8. The use of a higher transmit frequency not only improved resolution and boundary definition, but also lowered the magnitude of jitter errors and thus increased inclusion CNR relative to the 2.5 MHz reference image shown in (a). In the presence of axial target motion (b and f), inclusion CNR was dramatically reduced for the 4.4 MHz image, and the images from the two transmit frequencies are similar in terms of inclusion detectability. The images in the presence of transverse target motions (c,d,g,h) all show significant degradations in quality compared to their stationary reference images, and, for the velocities shown, the 2.5 MHz images are of higher quality than the 4.4 MHz images. Table 4 indicates that in the presence of elevation or lateral target motion, inclusion detectability will be greater at 2.5 MHz than at 4.4 MHz for even lower magnitude velocities than those shown in Fig. 8.

Approximate Motion Limits

Table 5 provides the approximate maximum uni-axial motion magnitudes that can be present to maintain high-quality ARFI imaging when radiation force displacement amplitude is small ($\sim 3 \mu\text{m}$). The magnitudes provided are applicable when displacements are tracked 0.9 ms following radiation force application. The choice of these values was based upon qualitative

inspections of image quality and inclusion detectability over the full range of simulated velocities. Although no strict quantitative criteria was used to determine these limits, the velocities shown generally correspond to an ARFI image SNR of about 10 dB (Table 2) and a inclusion CNR of roughly 1.4 (Table 4). The acceleration values listed correspond to a motion filter error of approximately 10%. It should be noted that values listed in Table 5 are approximate limits provided for insight, and true limitations will likely vary somewhat on a case-by-case basis. More elaboration on this matter is provided in the *Discussion* section of this document.

To provide perspective, Table 6 lists the maximum velocity and acceleration magnitudes reported in the literature for motion in the heart and for cardiovascular-related motion in the liver. These maximum magnitudes will likely be significantly larger than the mean temporal magnitudes. As ARFI imaging of an abdominal region of interest can be completed in its entirety during a single breath-hold, liver velocities and accelerations related to respiratory events have been ignored. The values listed for liver motion were extracted from data reported by Kolen et al. (2004), whereas the values listed for heart motion were reported by Price et al. (2000) and Cheung et al. (2005). In the authors' experience, we believe that there may be segments of the liver (particularly those near the heart) that experience peak velocity and acceleration magnitudes resembling those listed for cardiac tissue in Table 6.

Discussion

Implications of Results

The results presented in the previous section demonstrate that situations exist where physiological motion in the liver will significantly impact ARFI image quality. This is particularly true for the higher transmit frequency examined. The tighter beamwidths associated with higher transmit frequencies result in faster RF line decorrelation in the presence of physiological motion, particularly for movements in the transverse dimensions. The results of this study indicate that in the presence of large (but clinically relevant) magnitude velocities, the benefits of a high transmit frequency may be overshadowed by increased noise related to RF line decorrelation. Thus, for elasticity imaging in the presence of physiological motion, it may be beneficial to utilize an imaging system with low spatial resolution in order to retain high image quality. This finding may also have an impact on intra-cardiac or trans-esophageal cardiac elasticity imaging, where tissue motion can be severe and transmit frequencies can be on the order of 7 MHz (Hsu et al., in press).

Both to simplify the problem and to ease comparisons to previous theoretical and experimental results (Wagner et al., 1983; Ramamurthy and Trahey, 1991), much of this document has reported results related to uni-axial target motions. This strategy has allowed for the axis-dependent effects of physiological motion to be examined. For example, ARFI imaging is tolerant of large axial velocities, but the motion filter algorithm examined begins to fail in the presence of relatively low axial accelerations. The converse is true for motion in the elevation dimension, which minimally impacts motion filter performance but may increase the magnitude of the jitter errors associated with the tracking algorithm significantly. *In vivo*, true uni-axial organ motion (relative to the transducer orientation) will be rarely encountered, if at all. However, optimized transducer orientations may aid in maintaining high image quality if some prior information concerning tissue motion is available. For example, if a transverse tissue acceleration exists in the region of interest, a simple transducer rotation could shift the bulk of the velocity fluctuation into the elevation dimension and improve motion filter performance. Although not all acoustic windows (such as in cardiac applications) may allow for such rotation, when available this technique could prove to be a straightforward and effective imaging strategy.

In many instances, it is not necessary to image a tissue region continuously, and several snapshots visualized in real-time may suffice. In these situations, it may be possible to avoid time periods where physiological motion degrades image quality altogether. The motion magnitudes listed in Table 6 are expected peak values that are likely significantly larger than temporal average magnitudes in the same region. Using ECG-gated data acquisition, it may be possible to either avoid periods of significant motion or to acquire data during time windows where the coordinate axis of dominant motion is at least partially known and can be adjusted for. This may be particularly true when utilizing parallel receive techniques, which decrease acquisition times significantly without an accompanying decrease in image quality (Fahey et al., 2006). This approach may be well-suited for abdominal imaging or guiding interventional procedures, but less adept for cardiac applications.

The velocity magnitudes listed in Table 5 are approximations based upon simulated data, and *in vivo* image quality may deteriorate to an unacceptable level at slightly lower velocities. This is partially due to the fact that, as a first step, we chose to utilize a simplified tissue motion model which ignored tissue compression/expansion, rotation, and (non-radiation force-induced) shearing. All of these mechanisms would further decorrelate RF data lines used for tracking and lead to higher jitter levels in displacement estimates. To the authors' knowledge, literature quantifying shearing or compression due to cardiovascular-related liver motion does not exist. A study utilizing a heart model to investigate the contributions of tissue compression and shearing on ARFI image quality is underway.

The limitations specified in Table 5 are specific to both the radiation force displacement magnitude (focal peak $\sim 3 \mu\text{m}$) and the time of displacement estimate (0.9 ms after radiation force pulse) studied in this paper. The simulated push strength used in this study is typical for abdominal applications, and was chosen to match displacement amplitudes induced experimentally in tissue-mimicking phantoms. However, larger radiation force displacements will increase SNR in images of stationary objects and likely reduce the effects of motion-induced decorrelation on image quality. For other radiation force elasticity imaging methods (which may induce different magnitude displacements in tissue), the analytical techniques used in this study will produce slightly different motion limitations.

In the presence of target motion, the shape of an inclusion in an image may become distorted since, in practice, the entire 2D FOV is not interrogated simultaneously. The degree of distortion is a function of target velocity, the inclusion size, the tracking interval in each region, and other acquisition parameters. As the distortion phenomenon is complex, we have ignored distortion effects in the simulation data shown in Fig. 8 in an effort to simplify CNR analysis. In these simulations, the displacements in the entire imaging plane were induced and tracked simultaneously. To provide perspective for parameters related to Fig. 8, in the presence of a +5 cm/s lateral target velocity an inclusion with a 20 mm diameter would grow roughly 5 mm in horizontal diameter in a conventional ARFI image (acquisition time of 150 ms) and 1.7 mm in horizontal diameter in an ARFI image acquired with parallel receive tracking (acquisition time of 30 ms) (Fahey et al., 2006).

The simulation results presented in this paper neglect any target motion that occurs during the transmission of a radiation force pushing pulse. This assumption allowed for a significant reduction in computational requirements associated with FEM mechanical models. However, this motion is present in experimental data, and does not appear to significantly impact displacement amplitude in motion filtered images for velocities achievable by the translation stage. At higher velocities, it is possible that displacement amplitude could be slightly reduced, with a corresponding decrease in SNR.

The results detailed in this study reflect those encountered in a target with specific mechanical properties at a particular time following the incident radiation force pulse. The conditions under scrutiny were chosen for their relevance to abdominal imaging acquisition schemes currently employed. Since shearing under the tracking beam PSF decreases the correlation between RF lines used for tracking, any alteration affecting the speed of the shear waves induced by incident pulses of radiation force will have some impact on the results presented herein. Additionally, changing the lateral or elevation transducer f-numbers will correspond to a change in the transverse beamwidths of the tracking beams, and in turn will alter the rate at which RF lines decorrelate with physiological motion.

Improvement Strategies

In order to provide a concise analysis of the problem, thus far we have restricted our discussion to a simple linear motion filter and to a tissue-tracking algorithm that is by many metrics considered the best of those implementable in real-time (Pinton et al., 2006). More robust motion filters and/or motion compensation strategies may improve the accuracy of recovered radiation force displacement fields in certain situations. Also, if the real-time tracking constraint is removed, more sophisticated tracking algorithms may be utilized in an effort to increase image quality in the presence of physiological motion. The following paragraphs weigh the benefits and disadvantages of several of these strategies.

In the presence of target acceleration, the design assumptions of the linear motion filter fail and its performance suffers. In its ideal implementation, a cutoff time for the filter algorithm is chosen to correspond to the expected recovery time of target tissues. Alternatively, in the presence of ample target acceleration, this cutoff may be shifted earlier in time. Oftentimes this will decrease the magnitude of velocity fluctuation between the time $t = 0$ and the time used to determine an estimate of a (constant) target/transducer velocity. The consequence of the shift is an alteration of the true radiation force displacement magnitude in the post-filtered image, particularly in the near field. In many situations, this may be a fruitful trade-off if displacement artifacts are removed adequately. However, in abdominal applications, radiation force displacements are typically small due to path length/attenuation effects, and for axial accelerations away from the transducer, an early motion filter cutoff time will suppress the displacement magnitude further. In this scenario, the SNR of the filtered displacement image may fall to unacceptable levels.

A better solution for abdominal imaging applications is likely the development of more robust motion filters. A second order motion filter has been designed that assumes a constant tissue acceleration (including 0 cm/s^2 - the linear filter case), then uses a weighting scheme to remove displacements that are not deemed to be associated with applied radiation forces. Model-based approaches that alleviate the need to specify a cutoff time are also in development. Although further discussion of these algorithms is beyond the scope of this paper, preliminary results are encouraging and will be presented in a future publication. Research is also being performed to optimize motion filter parameters, such as the amount of pixel-averaging used to gather an estimate of target velocity, in order to improve performance.

Image quality in the presence of physiological motion may also be improved *via* more sophisticated tissue tracking algorithms. Perhaps the most obvious course of action is the utilization of multi-dimensional tracking methods. Tracking in the lateral or elevation dimensions would allow for motion filtering in these dimensions, as well as markedly increase the degree of transverse motion between RF lines that could be tolerated before image quality is affected. The downside to multi-dimensional tracking is a hefty increase in computational requirements, which prevents real-time image visualization even when using state-of-the-art computers. Multi-dimensional tracking may find use in diagnostic forums, but likely will hold

less utility for situations benefiting from instantaneous feedback, such as the guidance of interventional procedures.

A second feasible processing strategy involves cumulative displacement tracking. Real-time ARFI imaging calculates the displacement between a reference RF line and a single RF line acquired some time later (in this study, 0.9 ms). However, in most cases there are several intermittent lines of RF data acquired in the time period between these two lines. Tissue motion may result in significant decorrelation between the reference RF line and the RF line acquired 0.9 ms later, but each sequentially-acquired RF line will typically remain highly correlated to the RF line acquired immediately before it. The tracking algorithm could be run multiple times, incrementing the reference and tracking RF lines later through time with each iteration. A cumulative displacement estimate can subsequently be tallied and used to form an image. This method may improve image SNR in situations where motion effects are severe, but actually tends to increase the magnitude of jitter errors in displacement estimates for scenarios with little to moderate tissue motion. Again, increased computational overhead is an issue, particularly when using short pulse repetition intervals. Future work will evaluate the performance of cumulative tracking and other sophisticated algorithms in the presence of physiological motion and determine tissue velocity magnitudes at which these advanced algorithms might provide significant benefit.

Conclusions

The impact of physiological motion on ARFI image quality has been studied. Although results were derived for the ARFI imaging technique, the same principles apply to other radiation force elasticity imaging applications that track tissue displacements as well. For a specified radiation force displacement amplitude, tissue velocity and acceleration magnitudes leading to unacceptable image quality have been estimated. In liver tissues the bulk of physiological motions may be tolerated, but in some regions velocity and acceleration magnitudes may reach levels that will degrade image quality significantly. Axis-dependent motion effects have been identified, and strategies for image quality improvement have been suggested if some knowledge of tissue motion is available *a priori*. It has been demonstrated that, in the clinically relevant range of tissue velocities studied, a reduction in transmit frequency can correspond to an increase in inclusion detectability and overall image quality. Future efforts will expand on the results presented and seek to optimize image processing parameters in the presence of physiological motion.

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a

b

C

Figure 1.

Functionality of linear motion filter. (a) shows the tracked displacement when ARFI data are acquired in the presence of 4 mm/s axial target motion. Assuming target region has completely recovered from radiation force excitation after 2.3 ms (arrow), we use the displacement tracked at this time (circled data point) to estimate the displacement profile attributable to transducer and/or target motion (dashed line). In (b) the original tracked displacement profile (squares) is shown, as well as the radiation force displacement profile (circles) recovered by subtracting the dashed profile in (a) from the original displacement estimate. (c) shows performance of filter when data are acquired in the presence of a 5 mm/s² target acceleration.

Figure 2.
Curvilinear scanning geometry and associated coordinate terminology used in this document.

a

b

C

d

Figure 3. Qualitative validation of the liver motion model. (a) and (b) show normalized reference (stationary) experimental and simulated ARFI images, respectively. (c) and (d) show normalized experimental and simulated ARFI images acquired in the presence of 5 mm/s lateral target motion. Enclosed region in (b) corresponds to data provided in Table 2.

a

b

C

d

e

f

Figure 4.

Motion filter effectiveness in the presence of target acceleration. (a) and (d) show images in the presence of 10 and 40 cm/s^2 axial acceleration, respectively. (b) and (e) show images for 100 and 300 cm/s^2 lateral accelerations, and (c) and (f) show images with 100 and 300 cm/s^2 accelerations in the elevation dimension. All phantom targets were stationary at the time of radiation force application ($t = 0$). The ideal motion filter output is shown in Fig. 3(b). Region outlined in (a) corresponds to statistical analysis shown in Table 1.

a

b

Figure 5.

Effect of initial target velocity on motion filter performance in the presence of target acceleration. (a) shows a filtered image with an initial axial velocity of 2 cm/s and an axial acceleration of 10 cm/s². (b) shows a filtered image with an initial lateral velocity of 2 cm/s and a lateral acceleration of 100 cm/s².

a

b

Figure 6.

Effect of target velocity on image quality parameters with a 2.5 MHz transmit frequency. (a) shows results for normalized cross-correlation coefficient, (b) shows results for jitter. Results shown are for a scan line near the left-hand side of the image (-12°). Error bars represent ± 1 standard deviation from the mean.

Figure 7.

ARFI image SNR vs. time of displacement estimate. Shown are SNR values for the stationary phantom, a phantom with a 5 cm/s lateral velocity, and a phantom with a 10 cm/s elevation velocity. All times are relative to the end of the radiation force pulse. SNR values were calculated in the enclosed region shown in Fig. 3(b).

a

b

C

d

e

f

50

h

Figure 8.

Comparison of ARFI images of a simulated inclusion phantom at two frequencies. Top row shows images with a transmit frequency of 2.5 MHz, bottom row with transmit frequency of 4.4 MHz. Shown from left to right are images acquired in the presence of (a and e) no motion, (b and f) 10 cm/s axial target velocity, (c and g) 10 cm/s elevation target velocity, and (d and h) 5 cm/s lateral target velocity. Dotted-line boxes in (a) show regions in all images used for CNR calculations. All images shown are motion filtered. Spatial scale of images is shown in (e).

Performance of the linear motion filter in the presence of target acceleration. Data shown are percent errors in recovered displacement relative to the reference stationary phantom. Displacement data were averaged over the region outlined in Fig. 4(a). The zero acceleration case represents a target moving with a constant vector velocity of 0.87 cm/s.

Table 1

Motion Axis <i>Acc. Mag. (cm/s²)</i>	Motion Filter Effectiveness vs. Target Acceleration					
	Axial		Elevation		Lateral	
	10	40	80	100	40	100
<i>Pct. Error</i>	-6.9	-31.9	-65.3	1.2	0.7	4.6
					7.5	25.9
						0
						-0.5

ARFI image SNR in the presence of a range of target velocities. Shown are SNR values for the stationary case, uni-axial motions along each axis, and a multi-axis motion of 8.7 cm/s resulting from simultaneous 5 cm/s motion along each axis. SNR values were calculated in the enclosed region shown in Fig. 3(b) after motion filtering was performed.

Table 2

Vel. Axis Vel. Mag. (cm/s) SNR (dB)	ARFI Image SNR vs. Target Velocity					
	N/A	Axial	Elevation	Lateral	All	All
	0	5	10	5	10	8.7
	13.6	13.0	11.5	13.2	11.3	9.4
						0.43
						8.5

Magnitude of jitter errors for transmit frequencies of 2.5 and 4.4 MHz. Results are provided for the stationary (reference) case and for uni-axial target velocities of 5 cm/s in each principal direction.

Table 3

Tx Freq	Mean Jitter Magnitude vs. Frequency			
	Vel. Axis	No Motion	Axial	Lateral
	2.5 MHz	0.29 μ m	0.43 μ m	1.54 μ m
	4.4 MHz	0.24 μ m	0.51 μ m	1.78 μ m

CNR values for a stiff cylindrical inclusion embedded in a homogeneous background material for transmit frequencies of 2.5 and 4.4 MHz. Results are provided for the stationary target (reference) case and for uni-axial target velocities ranging from 2 - 10 cm/s.

Table 4

Inclusion CNR vs. Frequency and Target Motion									
	Vel. Axis		N/A	Axial		Elevation		Lateral	
	Vel. Mag. (cm/s)		0	5	10	5	10	2	5
Tx Freq	2.5 MHz		2.41	2.17	1.77	2.22	1.66	2.10	0.59
	4.4 MHz		3.34	2.34	1.20	2.12	0.78	1.54	0.26

Table 5

Approximate uni-axial motion limitations on ARFI imaging. Shown are velocity and acceleration limits for a 2.5 MHz transmit frequency and velocity limits for a 4.4 MHz transmit frequency. Magnitudes shown were determined for a peak radiation force displacement magnitude of approximately $3\text{ }\mu\text{m}$ in the focal zone. Results are specific to displacements tracked 0.9 ms following the removal of radiation force.

Approximate Uni-Axial Motion Limitations				
Criterion		Axial	Elevation	Lateral
	<i>Vel., 2.5 MHz</i>	20 cm/s	10 cm/s	3 - 4 cm/s
	<i>Vel., 4.4 MHz</i>	8 cm/s	6 - 7 cm/s	2 cm/s
	<i>Acc., 2.5 MHz</i>	20 cm/s ²	300 cm/s ²	>100 cm/s ²

Table 6

Expected maximum velocity and acceleration magnitudes for heart and liver motion. Liver data shown neglects respiratory-induced motions and thus reflects motions related to cardiovascular events. Values indicated are maximum expected magnitudes, and are likely significantly larger than the mean temporal magnitudes. Values listed for liver motion were extracted from data reported by Kolen et al. (2004); values for heart motion were reported by Price et al. (2000) and Cheung et al. (2005).

Peak Expected Motion Magnitudes			
		Velocity	Acceleration
Organ	Liver-cardio.	2 - 3 cm/s	50 - 60 cm/s ²
	Heart	> 16 cm/s	190 cm/s ²