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Acoustic Radiation Force Impulse (ARFI) Imaging-Based Needle Visualization

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Abstract

Ultrasound-guided needle placement is widely used in the clinical setting, particularly for central venous catheter placement, tissue biopsy and regional anesthesia. Difficulties with ultrasound guidance in these areas often result from steep needle insertion angles and spatial offsets between the imaging plane and the needle. Acoustic Radiation Force Impulse (ARFI) imaging leads to improved needle visualization because it uses a standard diagnostic scanner to perform radiation force based elasticity imaging, creating a displacement map that displays tissue stiffness variations. The needle visualization in ARFI images is independent of needle-insertion angle and also extends needle visibility out of plane. Although ARFI images portray needles well, they often do not contain the usual B-mode landmarks. Therefore, a three-step segmentation algorithm has been developed to identify a needle in an ARFI image and overlay the needle prediction on a coregistered B-mode image. The steps are: (1) contrast enhancement by median filtration and Laplacian operator filtration, (2) noise suppression through displacement estimate correlation coefficient thresholding and (3) smoothing by removal of outliers and best-fit line prediction. The algorithm was applied to data sets from horizontal 18, 21 and 25 gauge needles between 0–4 mm offset in elevation from the transducer imaging plane and to 18G needles on the transducer axis (in plane) between 10° and 35° from the horizontal. Needle tips were visualized within 2 mm of their actual position for both horizontal needle orientations up to 1.5 mm off set in elevation from the transducer imaging plane and on-axis angled needles between 10°–35° above the horizontal orientation. We conclude that segmented ARFI images overlaid on matched B-mode images hold promise for improved needle visibility in many clinical applications.

Keywords

ARFI imaging; nerve; radiation force; regional anesthesia; ultrasound guidance; ultrasound image segmentation

INTRODUCTION

Ultrasound-guided needle placement is widely used in the clinical setting, particularly for central venous catheter placement, tissue biopsy and regional anesthesia. In fact, ultrasound-guidance has been recommended as the technique of choice for central venous access in Britain since 2002.¹ In both central venous catheter placement and regional anesthesia, traditional 2-D (B-mode) ultrasound-guidance has been shown to be more effective and to lead to fewer complications than the alternative landmark method (or nerve stimulation for peripheral nerve blocks).^{2, 3} However, difficulties remain in both of these areas when the

needle is not in an exactly-specified orientation to the transducer, nerve or central vein. The most important factors that determine the difficulty of needle visibility under ultrasound guidance are: (1) insertion angle, which is often too steep and mandated by anatomic structure distribution, (2) spatial offset between the imaging plane and the needle plane and (3) small needle gauge. These three factors can impede what many clinicians feel is the most important aspect of ultrasound guidance – visibility of the needle tip.^{4, 5} Modifications to needles used for regional blocks (such as coating, dimpling, photoacoustically exciting or vibrating for Doppler imaging) have been attempted to improve visualization but have not been implemented commercially.^{4, 6, 7} Clinicians also rely on the real-time nature of B-mode images and needle movement for visualization, but this does not always portray the needle tip.

While B-mode images are susceptible to these difficulties in needle visualization, Acoustic Radiation Force Impulse (ARFI) images provide the basis for improved visualization because ARFI image contrast is derived from differences in the mechanical properties of tissue, rather than the acoustic properties.⁸ ARFI images are generated using a diagnostic ultrasound system; thus, coregistered B-mode and ARFI images are acquired concurrently. ARFI images have been used to interrogate tissue structural and mechanical properties^{9, 10} and successfully distinguish stiffer inclusions where classical B-mode does not provide adequate contrast.¹¹ Needles appear in ARFI images as areas with lower displacement than their surroundings. Due to the high elastic modulus of steel compared to soft tissues (MPa to kPa), the acoustic radiation force is not expected to generate measurable deformations within the needle. We hypothesize that its relatively rigid nature influences the surrounding soft tissue deformation. In particular, where imaging angled needles in B-mode is challenged by specular reflection off of the needle away from the transducer, the local stiffening effect of the needle can be visualized with ARFI imaging. Likewise, when imaging needles are slightly out of the elevation plane, the local stiffening effect of the needle can be visualized within the ARFI imaging plane. While ARFI images provide enhanced needle contrast due to the much larger stiffness and fixed nature of the needle as compared to the surrounding tissue, they do not show the same vascular and nerve landmarks that clinicians look for when performing central venous catheter placement and regional anesthesia.^{11, 12} Combining the improved needle contrast from ARFI imaging and surrounding tissue information from B-mode would provide a clinically-useful tool for regional anesthesia, tissue biopsy and central venous access. An image-segmentation algorithm has been developed and applied to ARFI needle images, with the resulting needle prediction image superimposed on the matched, concurrently-acquired B-mode image. While clinicians can also rely on needle movement for visualization, this paper compares output of the ARFI-based needle visualization algorithm with still B-mode images.

The needle visualization algorithm developed herein relies on a combination of features from several existing image segmentation techniques. Image segmentation algorithms have traditionally been investigated in ultrasound to identify particular image features or segments of interest. Classically, they have depended on image pixel characteristics such as similarities and discontinuities in pixel brightness.¹³ Many segmentation algorithms rely on computationally-intensive approaches such as topological derivatives,¹³ active contour-based approaches¹⁴ or user-defined input,¹⁵ often in combination with *a priori* knowledge of the segmented feature.¹³ Classically-researched and computationally fast edge detection methods include first-derivative operators, including the Canny and Sobel operators,^{16, 17} the second derivative Laplacian operator¹⁶ and neural network-based approaches.¹⁸ Many of these have been applied to ultrasonic images as well as Doppler data¹⁸ and are well suited to ARFI displacement images because of the relatively high needle contrast. The Laplacian operator has the advantage of being simple to encode with greater contrast enhancement, although it can be affected by noise because it requires second-order derivatives.^{16, 19} The

Laplacian operator was chosen for this application because it can yield more exact edge detection than the first-order derivative operators (such as the Canny, Sobel and Prewitt operators).¹⁶ In this paper, we develop, implement and evaluate a Laplacian-based needle segmentation algorithm applied to ARFI displacement images of needles inserted in tissue.

METHODS

Image-segmentation approach

The image-segmentation algorithm developed to create an automated needle position estimate from ARFI images contains three major steps: (1) contrast enhancement, (2) noise suppression and (3) smoothing with edge preservation. The needle-location prediction derived from the ARFI image is then overlaid on the concurrently acquired B-mode image for clinician visualization. Figure 1 shows a schematic of steps involved in the needle - identification algorithm.

Contrast enhancement

Ultrasound images contain speckle, which can impede conventional edge detection.²⁰ While ARFI images do not contain the same speckle, identification of the needle can be complicated by tissue structure heterogeneities and displacement estimation jitter noise (for example salt and pepper noise^{8, 11}). Therefore, after standard image processing (such as depth- dependent gain correction), ARFI image-contrast enhancement was performed by utilizing thresholded Laplacian edge detection. Figure 2 provides images demonstrating the steps outlined below.

Laplacian operator—Most Laplacian-based ultrasound imaging edge detectors rely on low-pass filters to reduce noise prior to edge detection.^{16, 20} In applications such as fetal head detection²¹ and ovarian follicular wall segmentation,²² the underlying image has adequate contrast, so prior smoothing does not have a significant impact on edge detection.²⁰ In ARFI images, needles are visible with a high degree of contrast, so smoothing is performed prior to edge detection to reduce sources of noise such as jitter and tissue inhomogeneities. Typically, in B-mode segmentation, the Laplacian-of-Gaussian (LoG) method is used, which involves Laplacian filtration of a Gaussian-filtered image for noise reduction.¹⁶ In this work, a median filter (rather than a Gaussian filter) was used prior to the Laplacian operator because it is particularly effective in reducing ‘salt-and-pepper’ noise without removing image details.²³ The spatial dimensions of the median filter were 1.73 mm in the axial dimension and 0.88 mm in the lateral dimension, as determined empirically through visual inspection of a subset of 10 ARFI needle images.

The Laplacian operator applied to the normalized and median-filtered ARFI image is the two-dimensional equivalent of the second derivative, which is used to find the local maxima in gradient values (areas of highest contrast) by finding the zero crossing of the second derivative.²³ Using displacement values rather than merely the level of contrast between the needle area and the surrounding tissue could make the algorithm susceptible to stiff areas of tissue heterogeneity rather than the needle area itself, which is why the algorithm does not rely on *a priori* assumptions of tissue mechanical properties. The formula for the Laplacian of a function $f(x, y)$, is:

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \quad (1)$$

The second derivatives along the x and y directions are approximated using difference equations²³ as follows:

$$\frac{\partial^2 f}{\partial x^2} = f[i, j+1] - 2f[i, j] + f[i, j-1] \quad (2)$$

$$\frac{\partial^2 f}{\partial y^2} = f[i+1, j] - 2f[i, j] + f[i-1, j] \quad (3)$$

In image processing, these difference equations can be approximated as a mask:²³

$$\nabla^2 = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad (4)$$

We used an adapted negative Laplacian mask as implemented in MATLAB (MathWorks™, Natick, MA) to further emphasize the center pixel and areas of high contrast:

$$\nabla^2 = \begin{bmatrix} -0.2 & -0.8 & -0.2 \\ -0.8 & 5.2 & -0.8 \\ -0.2 & -0.8 & -0.2 \end{bmatrix} \quad (5)$$

After taking the Laplacian of the median filtered ARFI displacement image, the absolute value was taken to create a ‘contrast’ image. Then, a threshold (Φ) was applied in order to identify regions within high-contrast edges. Pixel values greater than Φ were set to 1 and pixel values less than or equal to Φ were set to 0, generating a binary image (Fig. 2c). The threshold was determined using:¹⁹

$$\Phi = \frac{\mu_1 - \mu_2}{2} \quad (6)$$

In Eq. (6), Φ is the threshold value and μ_1 and μ_2 are the mean pixel values (as outputted by the Laplacian filter) inside and outside of the needle, respectively. The threshold was determined through manual identification of the needle in a B-mode image and finding the corresponding mean ‘contrast’ image pixel values inside and out of the needle in a test set of 16 ARFI images per needle gauge. In the algorithm, this thresholding operation created a binary image with a likely needle region as identified within high-contrast Laplacian-identified edges (Fig. 2c). The global pixel threshold value was thus empirically determined to be $\Phi = 0.8$. The average μ_1 value was 1.99 ± 0.56 while the average μ_2 value was 0.37 ± 0.66 .

Noise reduction

The areas highlighted by the binary image typically portray the needle area but can include noise associated with spuriously-high contrast. Conveniently, the remaining noise has consistently been associated with poor, or noisy, underlying displacement estimates. In ARFI data, displacements are estimated using correlation-based methods.²⁴ The correlation

coefficients can be used to eliminate poor displacement estimates that result from noise, reverberations and air or fluid in the sample. Pixels associated with low cross-correlation coefficients were therefore set to zero in the binary needle prediction image with a correlation cutoff set at 0.999. This threshold was manually identified after testing the algorithm on a training set of 10 horizontal needle images and was not changed during the remaining experiments. The effect of this noise removal step can be seen in a comparison between figures 3a and 3b, particularly in the removal of the area associated with the water path near the surface of the transducer. Removal of poor displacement estimates is computationally faster at this step in the process because a binary image was created with the contrast threshold. Thus, the poorly-correlated areas can be assigned a background pixel value of zero rather than finding nearest neighbors to fill in poor estimates, which is a more computationally time-intensive process.

Smoothing/continuity constraint

Because needles are rigid bodies, one can use *a priori* knowledge of needle shape to generate a physically-realistic image from acquired data.¹⁶ In the case of needles and other linear objects, a simple way to perform smoothing involves fitting a line through the high-contrast points predicted from the threshold image. The continuity constraint was applied after noise reduction because the large continuous areas that remain are most likely associated with the needle. For this application, the binary prediction images as shown in figure 2c were subjected to a continuity constraint in the form of a best-fit line prediction. This line was set to have only the slope and tip location as degrees of freedom because the needles are known to be straight. In addition, because of reverberations and shadowing below the needle, this step included a depth cutoff in which binary image values greater than 1 mm below the top edge of the needle prediction were removed. The line was also assumed to extend to the edge of the image. First, the binary needle area estimate generated by the previous steps in the algorithm was used to generate a best-fit line. Then, an iterative removal of outliers as defined by the farthest point with respect to the previous best-fit line occurred until 75% of the original points were kept. This final best-fit line was used to predict the needle location and needle tip in the axial and lateral dimensions. Removing 25% of outliers was selected empirically after utilization of the algorithm with a test set but was not altered in the automated algorithm. The improvement in needle prediction image with outlier removal is shown in figure 3. The needle width displayed in the overlaid needle images (shown in red in figure 3c) represents the axial standard deviation of the needle prediction points after iterative outlier removal.

Registration with B-mode

Image registration is the construction of a composite medical image from overlapping images.²⁵ Often, this process involves a linear transformation between two images, although it can frequently require other processing if there is skewing of the images.²⁵ For the ARFI-derived needle mask and B-mode images, the consistent beam locations between the two image acquisitions means that the data sets are inherently coregistered, an advantage intrinsic to acquiring the B-mode and ARFI data sets with the same transducer. Depending on clinician preference, the mask can be opaque or transparent and can allow the clinician to view the needle relative to familiar B-mode landmarks. The needle mask was displayed in the registered B-mode image with a radius equal to the axial standard deviation of the needle prediction points. This radius was used for research purposes as another way to identify how many points were being kept in the continuity-constraint part of the algorithm but could be modified to represent the known needle diameters.

Experimental setup

200 Bloom gelatin and graphite tissue-mimicking phantoms were used for these experiments.^{8, 26} 18G, 21G and 25G (Becton Dickinson and Company, Franklin Lakes, NJ) needles (outside diameters 1.27 mm, 0.82 mm and 0.52 mm, respectively) were then inserted into the phantoms and imaged in two configurations – horizontal longitudinally – and the 18G needles were also examined at multiple angles to the horizontal. The horizontal longitudinal images were taken both on-axis and in fixed elevation increments off-axis to the transducer imaging plane, as shown in figure 4. In addition, data sets were acquired in degassed lean bovine muscle and during one *in vivo* brachial plexus injection experiment to examine the effectiveness of the algorithm. The *in-vivo* data set was acquired in a 39-year old male subject in compliance with Duke IRB#10201.

Experiments were performed with a Siemens SONOLINE™ Antares scanner with a VF7-3 transducer (Siemens Medical Systems, Ultrasound Group, Issaquah, WA). The system has been modified for user control of acoustic beam sequences and intensities, as well as allowing access to the in-phase and quadrature (IQ) data.²⁴

A Daedal Positioning Systems model 2525 rotatory positioning stage (Parker Hannifin Corp, Daedal Division, Irwin, PA) with a custom attachment was used to measure the angle of needle insertion to the horizontal.

Two ultrasonic imaging processes were used in this experiment: traditional B-mode and ARFI imaging. Two types of acoustic beams are used to generate ARFI displacement images: high-intensity pushing beams and conventional B-mode tracking beams.^{9, 27, 28} The beams had a center frequency of 5.33 MHz, were electronically laterally focused at 25 mm, with an F/2 focal configuration, and had a fixed elevation focus near 37 mm unless otherwise specified. To generate an ARFI image, a reference tracking beam is transmitted, followed by a pushing beam. The pushing beams are similar to color Doppler pulses but with unapodized apertures and longer pulse lengths (400 cycles) for a duration of 95 μ s. The pushing beam was followed by a series of 50 tracking beams at 5.33 MHz in typical A-line configuration transmitted at a pulse repetition frequency (prf) of 7 kHz for an overall tracking duration of up to 7 ms in each pushing location. The lateral field of view was 25 mm, obtained with 36 pushing locations spaced 0.71 mm apart and four parallel receive tracking beams with uniform lateral spacing of 0.18mm.²⁹

The transducer was held with a motorized translation stage (model NM 3000, 0.1 μ m precision, Newport Corporation, Irvine, CA). After alignment of the needle and imaging plane, the custom pulse sequence was transmitted and IQ data were stored for off-line processing. An additional B-mode image was stored as well for comparison with the ARFI data and registration.

Local displacement estimates were calculated using the Loupas phase-shift estimator^{24, 30} and the magnitude of the complex correlation coefficient was used for thresholding.³¹ The complete ARFI data set yields displacement estimates through time for a 2-D region of interest,⁹ with the corresponding correlation coefficient magnitudes. The 2-D ARFI needle images portray displacement estimates calculated 0.7 ms after the pushing beam.

Needle visualization algorithm implementation

The needle visualization algorithm was applied to data sets obtained using horizontal 18, 21 and 25 gauge needles at 16 locations on and elevationally off-axis to the transducer in .25 mm increments and to 18G needles on the transducer axis between 5° and 30° to the horizontal, as shown in figure 4. The algorithm-determined needle location was compared to the original ARFI images and B-mode images. In addition, after imaging, the phantoms

(with the needle in place) were bisected so that needle placement could be identified and photographed for use as the needle placement gold standard, as shown in figure 5.

RESULTS

Comparison to B-mode

Example overlaid binary 21G needle images with co-registered B-mode images are shown in figure 6 for various elevation offsets between the horizontal needle and transducer imaging plane. Figure 7 provides an example with a smaller (25G) needle. The algorithm was also applied to angled needles within the imaging plane (Fig. 8), to horizontal needles in degassed lean bovine muscle (Fig. 9) and to images obtained *in vivo* in a human volunteer (Fig. 10).

Quantitative metrics: needle tip visualization

Needle tip prediction accuracy is particularly important for clinical applications especially influencing success rate of intravenous catheterization and regional anesthesia and avoidance of damage to surrounding tissue structures. The rms distances between the tip prediction and actual tip location as a function of elevation offset from the transducer are shown in figure 11a for all needle gauges. The difference between the needle tip prediction algorithm output and the actual needle tip location can be viewed in the form of a polar plot. Figure 11b shows the root-mean-square (rms) error and angular position of the needle tip location prediction with respect to the center of the plot, which was the location of the actual needle tip in the axial-lateral plane of the bisected phantoms. Figure 12 shows the differences between needle tip prediction and needle tip location for the 18G needles inserted at various angles to the horizontal.

DISCUSSION

In the areas of regional anesthesia, central venous catheter placement and tissue biopsy, B-mode ultrasound has been useful to aid needle guidance, increase success rate and prevent injuries to surrounding tissues.^{2, 3} Currently, the clinician suffers from two primary difficulties with ultrasound needle guidance that are addressed by the algorithm presented here: visualization of needles that have elevation offset from the transducer imaging plane and visualization of needles at steep angles. In clinical settings, where a nerve or vessel has been visualized with B-mode but the needle can't be seen, this algorithm may be implemented for the clinician to determine the needle tip location. For regional anesthesia, central venous catheter placement and tissue biopsy, the needle tip should be visualized within the diameter of the object that the needle is targeting.³² Since the smallest targeted vessels, nerves and biopsy targets are generally greater than 2 mm in diameter,^{32, 33} an appropriate target for this algorithm would be for rms error within 2 mm. The accuracy of needle tip prediction using this algorithm (Figs. 11, 12) suggests that implementation would be a clinically- useful tool. As shown in figure 11, the algorithm performs particularly well with elevation offsets up to 1.5 mm away, where the needle tip prediction is likely to be within 2 mm of the actual needle tip location.

Figure 11 demonstrates the effectiveness of predicting the horizontal needle tip location for three different needle gauges with the automated needle segmentation algorithm. The algorithm performed well for all three needle gauges, yielding tip estimates 2 mm or closer to the actual needle tip location in the axial-lateral plane within 1.5 mm of the needle axis. While the algorithm performed worse for the 25G needle, the fact that this needle has the smallest outer diameter means that it is also the most difficult to see in traditional B-mode, so the improvement of the algorithm for visualization (as shown in figures 7 and 9) over

traditional B-mode is still substantial. An additional advantage of this algorithm is that the strict correlation coefficient and Laplacian filter output thresholds prevent it from generating false positive needle location estimates. While data sets were acquired up to 4 mm elevationally off-axis to the needle for all three needle gauges, the algorithm only yielded needle location predictions within 1 mm of the needle for the 21G and 25G needles and within 1.75 mm for the 18G needle. Therefore, when the algorithm portrays a needle, the clinician would know that they are within a specified distance of the actual needle plane.

Needles at angles to the horizontal in homogenous phantoms were also well-visualized with the images generated by the needle segmentation algorithm, as shown in figure 8. As one can see in figures 9(c) and (f)), angled needles in heterogeneous tissues such as muscle can be extremely difficult to see in B-mode images but the needle is clearly portrayed in the needle-algorithm overlaid image. Thus, identification of the needle tip to within 2 mm of its actual location provides a considerable improvement over B-mode imaging alone.

Because B-mode and ARFI images are 2D in nature while the needle tip prediction is close to the actual needle tip location in the axial/lateral plane, the out of plane dimension could introduce a needle-tip interpretation error. For applications to regional anesthesia and central venous access, however, the important information for the clinician is knowing where the needle tip is relative to other structures in the b-mode image. Having a needle-tip identification algorithm that can tell the clinician that the needle is close to a desired anatomic detail of interest (such as a nerve or vessel) will allow the clinician to easily shift the transducer to an on-axis view in which a nerve and needle can be visualized together in the B-mode image. While it may be challenging to move the needle in elevation toward the anatomic features of interest, this is an existing challenge for clinicians that will be lessened by the information this algorithm provides about the needle location. The needle identification algorithm can also be used by a clinician to find the on-axis plane because the needle will become visible only in imaging planes that are within 2 mm of the on-axis plane, as shown in figures 11 and 12.

The human and bovine muscle examples shown in figures 9 and 10 provide further evidence of future clinical utility of the algorithm. Since many nerves are anatomically located near muscle, the needle can often be confused with the horizontal muscle striations seen in b-mode images, a confusion that is particularly obvious in figure 9. Figure 10 demonstrates the utility of the needle segmentation algorithm in a clinical setting of an intrascapular injection of a subject's brachial plexus. While it appears that the actual needle extends beyond the segmented section, this is likely due to the fact that this image was acquired after 2 cc of saline were injected, leading to decorrelation around the needle tip that was probably masked during the decorrelation-removal step in the automatic algorithm. There are also several striations close to the surface that might be confused for the needle but the algorithm correctly identified the needle path. In some cases, there may be more tissue heterogeneity than that seen in figure 10, which may lead to false prediction points after binary thresholding of the laplacian operator output. However, these heterogeneous regions are unlikely to be as consistently stiff and linear as the needle path, so the iterative removal of outliers and line-fitting may be sufficient to identify the needle. Excessive physiologic or handheld motion could also affect the needle prediction through elimination of the needle-containing pixels in the correlation-coefficient thresholding step of the algorithm. While it is expected that the implementation of existing motion filtering techniques that have been described for *in-vivo* ARFI imaging³⁴ could improve the needle predictions in those cases, this would require further investigation.

While many existing ultrasound segmentation algorithms require user input,¹⁹ the needle visualization algorithm presented here is a fully automated approach based on underlying

features of the ARFI image. The contrast threshold was based on the assumption of a near Gaussian distribution of pixel values inside and outside the needle to generate a fixed global contrast threshold over all three needle gauges. In order to ensure automaticity, the contrast threshold was not adjusted in the remaining testing of the algorithm. The preset contrast, correlation coefficient cutoff, and smoothing functions create an algorithm that does not require real-time user input.

CONCLUSIONS

Information gleaned from ARFI images of needles in tissue can supplement traditional B-mode to provide clinically-useful needle visualization. The ease of registration to B-mode images, the robust nature of the needle identification algorithm and the lack of required user input make this algorithm well suited for translation to the clinical setting. Improvements in patient care can be achieved by identification of needle position, particularly in the areas of regional anesthesia, tissue biopsy and central venous access. The needle visualization algorithm can successfully identify needle tips to within 2 mm of their actual position up to 1.5 mm off-axis from the imaging plane. In addition, the needle visualization algorithm worked well for needle angles between 0° and 35°, with particular improvement over B-mode visualization in the more angled cases. This algorithm (perhaps with a modified smoothing function) may also be useful in identification of other implanted medical hardware, such as cardiac devices and brachytherapy seeds.

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FIG. 1.
Flowchart of ARFI-based needle identification algorithm.

FIG. 2.

Comparison of conventional B-mode image (a), ARFI displacement image (b) and output of the absolute value of the Laplacian operator with contrast thresholding (c). (c) has the binary image set to a pixel value of 1 (shown as white) and the background set to zero (shown as black). All images are of an 18G horizontal needle in a 200 Bloom graphite phantom aligned perpendicularly to the axial dimension and centered within the elevation dimension of the transducer (on-axis). See figure 4 for clarification of needle placement with reference to transducer location.

FIG. 3.

Noise removal and smoothing of binary needle prediction images through application of a continuity constraint. The binary thresholded Laplacian image (a) is subject to a noise reduction step through correlation coefficient thresholding (the output of which is shown as the blue area in (b)). The binary prediction image output from the contrast enhancement and noise reduction steps is subject to the continuity constraint line of best-fit without removal of outliers (the red line in (b)). The best-fit line is shown through the needle prediction points after the iterative removal of outliers (c). The needle prediction image overlaid with the B-mode image (d). In (d), the needle is shown as having the width equal to the axial standard deviation of the needle prediction points after iterative outlier removal. Images are of an 18G needle 2.25 mm off-axis in elevation from the transducer imaging plane. This data set was acquired in excised, degassed, lean bovine muscle.

FIG. 4.
Diagram of experimental setup.

FIG. 5.

The needle tip was identified by measuring the lateral and axial distances of the tip from the edges of the phantom in the needle imaging plane in both the on-axis B-mode image (a) and the bisected phantom with ruler hash marks 1 mm apart (b). Once the measurements were made, the location was determined in the B-mode images using the distance from the top and lateral edge of the phantom. (c) shows the overlaid needle tip prediction to which the measured tip location was compared.

FIG. 6.

B-mode images of a horizontal 21G needle in a 200-Bloom graphite phantom at several locations elevationally off-axis from the transducer without (top row) and with (bottom row) needle visualization algorithm applied. Column 1 ((a) and (d)) shows no elevation offset from the transducer (on-axis), column 2 ((b) and (e)) shows a 0.5 mm elevation offset, and column 3 ((c) and (f)) shows a 1 mm elevation offset. The green X in each image of the bottom row shows the location of the needle tip as determined by bisecting the phantom in the needle imaging plane.

FIG. 7.

Visualization of a horizontal 25G needle in a 200 Bloom graphite phantom on-axis. (a) shows the B-mode image while (b) shows the B-mode with needle visualization overlay. The green X shows the location of the needle tip as determined by bisecting the phantom in the needle imaging plane.

FIG. 8.

B-mode images of an angled 18G needle in a 200 Bloom graphite phantom at different angles with respect to the horizontal without (top row) and with (bottom row) needle visualization algorithm applied. Column 1 ((a) and (d)) shows a 10° angle above the horizontal, column 2 ((b) and (e)) shows a 16° angle, and column 3 ((c) and (f)) shows a 32° angle. The green X in each image of the bottom row shows the location of the needle tip as determined by bisecting the phantom in the needle imaging plane.

FIG. 9.

B-mode images of needles in degassed lean bovine muscle (top row) and with needle visualization algorithm applied (bottom row). Column 1 ((a) and (d)) shows a 21G needle . 75 mm elevationally off-axis from the transducer, column 2 (Figs. (b) and (e)) shows a 25G needle 1.5 mm off-axis from the transducer, and column 3 ((c) and (f)) shows an on-axis 18G needle at a 30° angle of insertion to the horizontal.

FIG. 10.

Visualization of an *in vivo* intrascapular injection after 2 cc injection of saline. (a) shows the B-mode image, while (b) shows the ARFI displacement image with the removed decorrelated areas shown in blue. (c) shows the needle overlay. Because these data sets were acquired after 2 cc of saline injection, we can see from (b) that the decorrelation-removal step removed the area where the injectate had infiltrated, leading to the underprediction of the apparent needle length as visualized in the B-mode image.

FIG. 11.

(a) RMS error of tip prediction versus elevation offset from the transducer. While measurements were acquired up to 4 mm offset from the transducer imaging plane, the distances shown are those that successfully generated a needle tip prediction image. (b) distribution of actual needle tip location versus needle tip prediction across all elevation offset distances in the lateral/axial plane for the three needle gauges. The radial projections to each point from the center of the polar plot indicate the direction and magnitude of the error. The magenta circle represents a 2 mm radius around the actual needle tip position and the arrows represent the mean tip prediction error for each needle gauge. The color-coding is consistent with the legend between (a) and (b).

Fig 12.

(a) RMS error of tip prediction versus needle insertion angle for four angled acquisitions. (b) distribution of actual needle tip location versus needle tip prediction across all angles of needle insertion with the actual needle tip location at the center of the plot. The magenta circle represents a 2 mm radius around the actual needle tip position. Images were acquired of 18G needles in a 200 Bloom graphite phantom at several angles to the horizontal within transducer imaging plane. The color-coding is consistent with the legend between (a) and (b).