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Relative Elastic Modulus Imaging Using Sector Ultrasound Data for Abdominal Applications: An Evaluation of Strategies and Feasibility

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Abstract

We reconstruct the elastic modulus distribution for one tissue mimicking (TM) phantom and two *in vivo* biopsy-confirmed liver tumors using curvilinear ultrasound echo data. Spatial distribution of the relative elastic modulus values is determined by solving an inverse problem within a region of interest (ROI). This inverse problem solution requires knowledge of the ultrasonically-measured displacement field in a uniform rectilinear grid to ensure that the resolution on the resultant relative elastic modulus elastogram will be uniform over the entire ROI.

Taking advantage of a new speckle tracking algorithm, two different displacement tracking strategies are investigated: (1) sector-shaped ultrasound data were converted to ultrasound data on a rectilinear grid prior to speckle tracking and (2) axial and lateral displacements directly obtained from sector-shaped data were converted to vertical and horizontal displacements on a rectilinear grid after speckle tracking. As compared to strain elastography (SE), TM phantom results show that relative elastic modulus imaging (REMI) using Strategy 2 provided higher contrast-to-noise ratios (>300% and 25% increases as compared to SE and REMI using Strategy 1, respectively). Furthermore, in phantoms, REMI using Strategy 2 more accurately (a 1.3% difference to SWE measurements) estimated the elastic contrast ratio between the target and the background, as compared to both SE (20–25%) and REMI using Strategy 1 (4.1%). It was also observed that relative modulus elastograms were more consistent to anatomical structures visualized on corresponding B-mode images for the two *in vivo* liver cases. Overall, we conclude that applying

REMI is feasible for abdominal organs such as the liver. Strategy 2 offered improved and consistent results for data investigated.

Keywords

Ultrasound Elastography; Relative Elastic Modulus Imaging; Speckle Tracking; Thermal Ablation

I. Introduction

Early developments in ultrasound quasi-static elastography [1–3] were focused on strain elastography (SE). The potential of SE for clinical imaging has resulted in several major vendors (*e.g.*, General Electric, Siemens, Philips *etc.*) releasing commercially-available real-time SE packages. Besides characterizing breast [4–6] and thyroid lesions [7, 8] using high frequency linear array transducers, clinical applications of SE have been expanded into monitoring thermal ablation therapies for liver cancers [12–14], diagnosing diffuse organ diseases such as liver cirrhosis [9], assessing risks for pre-term birth [10] and cardiac elastography [11].

Relative Elastic modulus imaging (REMI) is considered to be a further development of ultrasound SE. Mathematically, given a ultrasonically-measured displacement field everywhere in an isotropic, nearly incompressible and elastic solid, the image reconstruction process in REMI determines the relative Young's modulus distribution of tissue being imaged as an inverse problem solution [12]. However, because the absolute force information cannot be obtained using conventional ultrasound equipment, only relative modulus information can be obtained through the above-mentioned reconstruction process. REMI has recently been extended to assess tissue nonlinearity in breast tissues [13, 14]. Positive outcomes have also been achieved when the REMI technique was applied to age assessment of DVT [15], differentiation of breast lesions [13, 14], monitoring thermal ablation therapies [12, 16] and detection of prostate cancer [17]. Generally, interpretations of elastic modulus elastograms are easier because they are not subject to the uniform stress assumption for SE. In fact, our early work [16] in a pre-clinical animal study using linear array transducers has demonstrated improved detectability of thermal ablation zones, as compared to that provided by strain elastograms.

In addition to SE and REMI, other elastographic modalities including acoustic radiation impulse imaging (ARFI) [18], shear wave elastography (SWE)/supersonic shear imaging (SSI) [19], and sonoelastography [20] have also been successfully used for monitoring liver ablation. Nevertheless, REMI appears to be one of the promising techniques among this cohort for monitoring thermal ablation therapies. Comparisons of these elastographic modalities can be found in a recent survey paper [21].

Our on-going effort in this paper is to translate the above-mentioned REMI technique into a clinical setting for providing image guidance for hepatic thermal ablation therapies. In order to do so, feasibility of REMI using curvilinear array transducers has to be addressed because curvilinear or phased array transducers are often used to achieve large sonographic windows for abdominal organs and cardiac applications. However, use of curvilinear array transducers

in conjunction with REMI is challenging primarily because of the difficulties in reliable tracking of tissue motion using sector-shaped ultrasound data. Recall that ultrasonically measured displacements are used as the input to reconstruct the underlying elastic modulus distribution. Consequently, the quality of the displacement input largely determines the outcome for REMI.

As compared to linear array transducers, curvilinear or phased array transducers have relatively low resolution (lower center frequency) and low signal-to-noise ratios at increased depths, posing difficulties for accurate ultrasonic speckle tracking. Out-of-plane tissue motion or subtle changes in the imaging plane associated with free hand scanning could also potentially result in large tracking errors due to significant signal de-correlation. Evidently, the quality of strain elastograms using curvilinear array transducers is sub-optimal as demonstrated by others using a commercial real-time SE package [22].

In a closely related study by Mousavi *et al.* [17], a different modulus inversion algorithm was applied in conjunction with trans-rectal ultrasound data to visualize *in vivo* prostate lesions. In addition to using a different modulus inversion formulation, in this study, we are particularly interested in speckle tracking strategies for REMI given sector-shaped ultrasound data. Although ultrasonic speckle tracking with sector shaped data has been investigated [23, 24]), those previous efforts were not for the purpose of reconstructing modulus elastograms.

Toward this end, the primary objective of this study was to investigate strategies that can reconstruct relative modulus elastograms using sector-shaped ultrasound-data. Contributions are twofold: (1) an evaluation of two different strategies for image formation of the (relative) elastic modulus elastograms using a comparison against each other and with SE, and (2) a demonstration of feasibility of REMI in a set of *in vivo* liver tumor data acquired in human patients. Our goals were accomplished by qualitatively and quantitatively comparing the quality of strain and (relative) elastic modulus elastograms using tissue-mimicking (TM) phantoms and *in vivo* ultrasound data containing biopsy-confirmed liver tumors. We have also quantified discrepancies and sought to identify their potential causes in the last section of this paper.

II. Methods and Materials

For both Strategies 1 and 2, the proposed workflow involves multiple steps (see Fig. 1). These, along with the interactions with speckle tracking [25] and the relative modulus inversion [12] algorithms are briefly presented in this section.

As shown in Fig. 1, the starting point is a pair of pre- and post-deformation ultrasound radiofrequency (RF) echo frames which are in a polar (sector-shaped) coordinate system. This is the same for both strategies. One key element of the proposed REMI algorithm [12] is to obtain ultrasonically-measured displacement fields in a rectilinear grid, as shown in Fig. 1 (see the plots in the third column). The main reason for requiring displacement inputs on a uniform rectilinear grid is that the uniform grid is equivalent to a constant size for all

(finite) elements during the finite element-based image reconstruction, thereby implying a consistent (image) resolution throughout the entire elastic modulus elastogram.

A. Differences between Strategies 1 and 2

In Strategy 1, RF echo data acquired from a polar coordinate system were first projected onto a Cartesian coordinate system through cubic interpolation. This process is known as scan conversion of the ultrasound signals. Both the pre- and post-deformation RF echo frames were scan-converted. Speckle tracking (Section II.B) was performed on the scan-converted RF echo data. Consequently, the estimated displacement vectors ($d\hat{x}, d\hat{y}$) are already generated on a uniform rectilinear coordinate system.

In Strategy 2, speckle tracking was first performed directly on the pair of pre- and post-deformation RF echo frames in a polar coordinate system. After speckle tracking, the corresponding displacement vector (dx, dy) is also in a polar coordinate system, where dy and dx are axial (parallel to the acoustic beam direction) and lateral (perpendicular to the acoustic beam direction) displacement components, respectively. Please note, that axial and lateral directions throughout this paper refer to the axial and lateral direction of the original sector-shaped ultrasound data (*i.e.* the first column of Fig. 1). In order to obtain displacement vectors ($d\hat{x}, d\hat{y}$) on a uniform rectilinear coordinate system, axial and lateral displacements were transformed using procedures illustrated in Fig. 2 below.

Speckle Tracking Method—In both strategies, a quality-guided block matching (QBM) method [26] was first used to obtain displacement vectors at an integer level from a pair of pre- and post-deformation RF echo frames. In Strategy 1, these RF frames were first scan-converted, while Strategy 2 used the original RF echo frames in polar coordinates. Similar to the classic block-matching algorithm, the QBM algorithm was also designed to match patterns in the pre-deformation RF echo frame with patterns in the post-deformation RF echo frame using a finite-sized search kernel (approximately 4 mm [lateral or horizontal] $\times$ 2.5 mm [axial or vertical]). More specifically, the QBM algorithm first creates a short list of high quality displacement estimates in a coarse grid, and then used these high quality displacement estimates to guide subsequent speckle tracking using a predictive search strategy [27]. The final density of displacement estimation varied slightly but was on the order of 0.15 mm (axial or vertical) $\times$ 0.15 mm (lateral or horizontal) for both strategies. In both strategies, RF echo signals were up-sampled in order to achieve the designated density of displacement estimation. Once all integer displacement vectors are obtained, sub-sample displacement estimation was performed using a new method [25]. This new sub-sample method modeled the correlation function between the pre- and matched post-deformation RF echo segments using a linear system description [28–30]. Consequently, an isocontour of the log-compressed correlation function mentioned above is an ellipse and therefore, finding the sub-sample displacements is equivalent to estimating the center of the ellipse in a least-square sense. More details of this speckle tracking method can be found elsewhere [25].

B. Strain Estimation

Once the final axial and lateral displacements, $d\hat{y}$ and $d\hat{x}$, were obtained using either Strategy 1 or Strategy 2, the displacement fields in both directions were first re-sampled onto

a uniform rectilinear grid (0.15 mm [vertical] $\times$ 0.15 mm [horizontal]). We use a vertical and horizontal strain notation for the rectilinear grid because, for the sector-shaped polar coordinate, the axial and lateral directions are different from the vertical and horizontal direction. Finally, local vertical and horizontal strains were separately estimated using a low-pass digital differentiator (*i.e.* Savitzky-Golay filter) described by Luo *et al.* [31]. The length of the low-pass differentiator was 3 mm for all cases investigated.

C. Relative Elastic Modulus Inversion (REMI) Algorithm

The REMI algorithm [12] modified from [32] is a finite element-based (FE) iterative reconstruction algorithm where the relative elastic modulus distribution is solved as a constrained minimization problem,

$$J_{\alpha}(\hat{E}) = \arg \min \left\{ \frac{1}{2} \|T(\hat{E}) - U\|^2 + \gamma V(\hat{E}) \right\}, E_{\min} \leq \hat{E} \leq E_{\max} \quad (1)$$

where $\hat{E}$ denotes the estimated modulus distribution and U is the ultrasonically estimated vertical and horizontal displacements as described in Section II-C. $T(\hat{E})$ are the predicted axial displacements by a forward FE simulation and $V(\hat{E})$ is a regularization function to penalize estimation based on image smoothness constraints. Consequently, the ultrasonically-estimated displacement field $U = \{d\hat{x}, d\hat{y}\}$ from Section II-B is used as the input to reconstruct relative modulus distribution (see Eqn. (1)). In other words, the image reconstruction process in REMI is to determine the relative elastic modulus distribution that when used in a forward FE solver gives the best match to the observed displacement field $\{d\hat{x}, d\hat{y}\}$. To obtain a relative elastic modulus image, the basic procedures involved are summarized as follows:

1. Estimate horizontal and vertical displacements from a region of interest (ROI; see the block box in the third column of images in Fig. 1) defined by a user.
2. Assume an initial uniform Young's modulus distribution. Displacements at the edges of the ROI will be enforced as boundary conditions to solve the 2D (plane stress) FEA forward solution.
3. Compare these predicted displacements U with the ultrasonically measured displacements $\{d\hat{x}, d\hat{y}\}$. Simultaneously, the assumed modulus distribution is updated to reflect this comparison. Iterations between Steps (2) and (3) continue until one of the two convergence criteria are satisfied: $J(\hat{E}) < \epsilon$ or $d\hat{E}_{k+1} < \epsilon$, where $d\hat{E}$ is the difference in the modulus distributions between two consecutive iterations and ϵ (10^{-6} in this study) is a predetermined threshold. Convergence was typically reached within 30 iterations.
4. Once convergence is reached, all modulus values within the ROI will be normalized by an averaged modulus value from a small area (typically 5 mm by 5 mm) identified by the user as normal liver tissue. This step converts all of our results to relative elastic modulus images.

For both strategies, ultrasonically-measured displacement fields were down-sampled to a uniform grid of 41×41 covering the entire of ROI. Thus, the (finite) element size was approximately $1.5 \text{ mm} \times 1.5 \text{ mm}$. The optimization toolbox in MATLAB (version 2015b, Mathworks Inc., MA, USA) was used to solve Eqn. (1). More details of this REMI method can be found in a previous publication [12].

D. Experimental validation

The two different strategies were evaluated by using TM phantom data and *in vivo* liver tissue data. In the first test, one TM phantom was used. The TM phantom contains one (slightly) stiff spherical target (14 mm diameter) in a large ($10 \text{ cm} \times 10 \text{ cm} \times 10 \text{ cm}$) background. The phantom was manufactured by Prof. Ernest Madsen at the University of Wisconsin-Madison, and procedure is described elsewhere [33, 34]. RF echo data were acquired using a Siemens S2000 Antares (Siemens Medical Solutions [USA] Inc., Mountain View, CA). The phantom was manually compressed using a curvilinear 6C1 HD curvilinear transducer (Siemens 6C1 HD) approximately to reach frame-averaged strains of roughly 1.5% during the data acquisition. The second study utilized two sets of *in vivo* biopsy-confirmed liver tissue data obtained using external free hand compressions of the liver. Under a protocol approved by the University of Wisconsin-Madison IRB, *in vivo* freehand ultrasound examinations were performed by a radiologist using a Siemens SONOLINE Antares ultrasound scanners equipped with a curvilinear array transducer (CH6-2), prior to their scheduled liver biopsies. Patient consent was obtained prior to any research scanning. In both cases, patients were instructed to hold the breath for 30 seconds while being scanned ultrasonically.

All RF echo data used in this study were sampled at 40 MHz and were acquired using the AXIUS Direct Ultrasound Research Interface (URI) software package [35]. Of note, freehand scanning was used for all patient data acquisitions using curvilinear transducers pulsed at 4.0 MHz.

Under B-mode imaging guidance, shear wave speeds were also measured in the above-mentioned TM phantom using a shear wave elastography (SWE) package using a clinical ultrasound scanner (Aixplorer®, Supersonic Imagine Inc., France). A system's quantification tool, known as "Q-Box™", was used to quantify stiffness values. More specifically, the Q-Box defined a circular ROI whose diameter was 4 mm and positioned over the stiffer target and the uniform background, respectively. A 12 MHz linear array transducer was used. Mean shear wave speeds over the two above-mentioned ROIs was automatically calculated by the Aixplorer scanner in m/s. The measured shear wave speed c was converted to shear modulus G using the following equation:

$$c = \sqrt{G/\rho} \quad (2)$$

where ρ is the mass density of the TM material (approximately 1.0 g/cm^3 [33, 34].

E. Data Analysis and Evaluation

Two metrics were chosen to compare REMI performance between Strategies 1 and 2. The first metric is the weighted

$$\text{CNR} = \frac{|I_t - I_b|}{\sqrt{w_t \sigma_t^2 + w_b \sigma_b^2}} \quad (3)$$

where I and σ^2 denote means and variances of signals, and subscripts b and t represent the background and the target, respectively. To calculate CNR using Eqn. (3) for each strain and modulus elastogram, the target was manually-segmented and the rest of the strain or modulus elastogram represented as the ‘background’. w is a weighting of either the target area or the background area to the total area, and is given by $w_x = \text{area}_x / \text{area}_{\text{total}}$, $x \in b, t$. Consideration of the weighted area is necessary because the target and the background contribute differently to the noise estimates [36].

The second metric is the elastic contrast (EC) which is defined as follows,

$$\text{EC} = \frac{I_t}{I_b} \quad (4)$$

where I denotes the mean values of intensity from regions of interest (ROIs) on the elastogram, and subscripts b and t represent the background and the target, respectively. Three different methods for ROI selection were used as shown in Fig. 3a–c. In Fig. 3, the middle rectangular or circular ROI within the target (delineated by the contour in orange in Fig. 3a) was used to calculate the mean intensity of the target, while small squares (Fig. 3a–b) or the large shaded blue ring (Fig. 3c) were used to calculate the mean intensity of the background. The area of the target ROI is equal to its counterpart in the background.

The “true” elastic contrast between the target and the background of the TM phantom was calculated based on shear modulus values converted from SWE measurements (Eqn. 1).

All data analyses were done off-line on a Windows-based Quad-CPU (2.8-GHz) mobile workstation (Lenovo W540, Lenovo Inc., NC, USA) equipped with 8-Gbytes of memory using ANSI C and the MEX interface to MATLAB.

III. Results

Figure 4 shows elastographic results (displacements, strain and [relative] elastic modulus) for the TM phantom. Particularly, the vertical and horizontal displacements computed using Strategy 1 contained higher levels of noise when compared to those computed using Strategy 2 (*i.e.* Fig. 4b vs. Fig. 4c and Fig. 4f vs. Fig. 4g). Because ultrasonically-measured displacements contain fundamental information, noise contained in the vertical and horizontal displacement field manifested itself into the corresponding vertical and horizontal

strain elastograms. Consequently, visually, the vertical and horizontal strain elastograms computed from Strategy 1 was slightly noisier than corresponding strain elastograms computed from Strategy 2 (see Fig. 4d vs. Fig. 4e and Fig. 4h vs. Fig. 4i). Similarly, the elastic modulus elastogram computed using Strategy 2 (Fig. 4k) also contained lower noise artifacts as compared to that computed using Strategy 1 (Fig. 4j).

The displacement estimation density in the speckle tracking algorithm (Section II.B) was varied to change the estimation density during the speckle tracking (see Fig. 1) for the TM phantom. Consistent with the visual perception obtained from Fig. 4, Figs. 5a and 5b show that the estimated CNR values of vertical strain and modulus elastograms from Strategy 2 were slightly higher than those computed using Strategy 1. It is also important to note that CNR values of relative elastic modulus elastograms were considerably higher when compared to that on the vertical strain elastograms. Overall, the mean CNR values of vertical strain elastograms (Fig. 5a) are 1.0 and 1.1 for Strategies 1 and 2, while the mean CNR values of relative modulus elastograms (Fig. 5b) are 2.7 and 3.7 for Strategies 1 and 2, respectively. It is important to note that, using Strategy 2, CNR values of resultant elastic modulus elastograms obtained were consistently higher (more than 3X) higher than the CNR values of resultant horizontal strain elastograms, regardless of the displacement estimation density.

As shown in Table I, using the SWE measurements as a gold standard, the mean errors of SE are 25.4% and 20.9%, for Strategies 1 and 2, respectively. The mean errors with REMI were significantly lower, and were 4.1% and 1.3% for Strategies 1 and 2, respectively. Overall, REMI obtained from Strategy 2 provided the closest match to the elastic contrast ratio obtained with SWE, though the difference is small (2.8%), as compared to REMI obtained using Strategy 1.

Images in the left column and right column of Fig. 6 were obtained using Strategies 1 and 2, respectively. Figs. 6d and 6e show vertical strain elastograms of a high grade neuroendocrine liver tumor. The tumor margins were not well delineated in either of the vertical strain elastograms. However, the lesion is clearly visible in both elastic modulus elastograms (Figs. 6j and 6k), regardless of the reconstruction strategy used. There were signs of motion tracking failures from displacements estimated using both strategies (*e.g.* Figs. 6b–c and 6f–g). Nevertheless, vertical displacements obtained using Strategy 2 was smoother than vertical displacements obtained using Strategy 1, indicating better quality in displacement estimation.

Fig. 7 shows a B-mode image and corresponding elastographic results for a Hepatocellular Carcinoma (HCC) in the liver. Similar to that shown in Figs. 6d–e, the tumor margins were not well delineated by either of the vertical strain elastograms (Figs. 7d and 7e). However, the lesion is clearly visible in the elastic modulus elastogram reconstructed using Strategy 2 (see Fig. 7k). Fig. 7j indicates failure in the image reconstruction. Visually, both vertical and horizontal displacements estimated using Strategy 2 were also smoother than those displacements obtained using Strategy 1, though there were signs of motion tracking failures from displacements estimated using both strategies.

IV. Discussion

As we demonstrated in an early publication [16] using a linear array transducer, relative elastic modulus images have high CNR values when compared to those obtained from strain elastograms, thereby implying better detectability of the target. This result is also confirmed with sector-shaped ultrasound data in this paper. There are two reasons for this improvement. First, compared to strain, the relative elastic modulus images depict intrinsic material properties of the tissue being studied, thereby providing unambiguous information of tissue elasticity. Second, the image reconstruction process for REMI can be regarded as an effective means of image de-noising. Furthermore, as shown in Table I, the elastic contrast value between the background and the target using REMI, on average, is more consistent with those obtained through SWE measurements. Since the modulus of treated tissue may be related to ablation temperature [38, 39], the estimated relative elastic moduli may potentially provide additional information, e.g. thermal dosage or cell damage.

On the one hand, Strategy 1 first used scan-conversion to transform the sector-shaped data onto a rectilinear coordinate system. Scan-conversion worked well for displaying B-mode images. However, it posed problems for speckle tracking, particularly, for areas further away from the center line of the image plane (see Fig. 4b and 4f). We stipulate that, after the scan-conversion, phase information from the original ultrasound RF data may have been compromised at locations further away from the centerline due to the “ $\cos(\theta)$ ” effect. Because our REMI algorithm enforces the ultrasonically-measured boundary condition in the forward FE solution (see Eqn. 1), poor displacement estimates away from the center line negatively impacted the outcome of the proposed REMI method (see Fig. 7j and 7k).

On the other hand, Strategy 2 required us to transform original axial and lateral displacements to corresponding vertical and horizontal displacement components, as shown in Fig. 2. In order to maintain quality in the transformed vertical and horizontal displacements, the quality of (original) lateral displacements has to be reasonable. In this sense, Strategy 2 led to higher quality (vertical) displacement estimates partially due to the new sub-sample tracking algorithm [25], which provided better quality lateral displacements. In computer simulations, the new sub-sample tracking algorithm [25] reduces the error variance by a factor of 2, as compared to a quadratic subsample algorithm [25]. Overall, we believe that Strategy 2 resulted in high quality displacement estimates and therefore, is a better choice for subsequent REMI, given data investigated in this study.

The *in vivo* results (Figs. 6 and 7) showed that there were significant discrepancies between strain and relative modulus elastograms. Recall that a strain distribution may lose correlation to its underlying stiffness distribution if the assumption of (relatively) uniform stress distribution is not valid. Evidently, the resultant displacement fields were significantly different as compared to those in the TM phantom (e.g. Fig. 4c vs. Fig. 6c). This is why the *in vivo* results were not completely surprising because, due to complex tissue motion in the liver, the uniform stress assumption was likely violated. In our earlier publication [16], we demonstrate a similar phenomenon in an *in vivo* pre-clinical animal study.

Because ultrasonically-measured displacements are enforced as the (displacement) boundary condition in the forward FE solution, the outcome of REMI will also be influenced by the quality of displacement estimates. In the work by Mousavi *et al.* [17], they used a different iterative inversion algorithm which may have better immunity to the noise in displacement estimates, because their algorithm did not use the ultrasound tracked displacements as a boundary condition in the forward FE formulation, and they used a built-in Gaussian smoothing process. Increased noise and complexity in the displacement estimates in patients are clearly visible when compared to displacements from the TM phantom (*e.g.* Fig. 7c vs. Fig. 4c). This may explain why the image quality in strain elastography and REMI is still sub-optimal. In the future, continued development of better modulus inversion algorithms and improved capabilities for rapid data acquisition and volumetric ultrasound data will improve image quality of modulus inversion.

For the neuroendocrine liver tumor (Fig. 6), the appearance of the liver lesion in the B-mode showed a mixed echo-rich and echo-poor pattern, which is typical for neuroendocrine liver tumors [40]. The high (relative) modulus values appear to be consistent with the upper right echo-poor region. The HCC lesion on the other hand (Fig. 7) has a typically mixed hyper- and hypo-echoic regions on the B-mode image [41]. The highly elevated (8–10 times higher than the background) modulus values correspond with the hyperechoic region while the moderately elevated (5–6 times higher than the background) region corresponds to the hypoechoic part of the HCC tumor. Overall, in both tumors, elevated stiffness regions on relative elastic modulus elastograms were more consistent with the corresponding B-mode images (*e.g.* Fig. 6g vs. Fig. 6a), as compared to strain elastograms. Because data were acquired from patients who only undergo a biopsy, the underlying tissue properties are not known in both cases. This is one limitation of this study. More carefully planned follow-up clinical studies are needed in order to demonstrate radiological and pathological correlations.

V. Conclusion

In this work, we have evaluated two strategies for displacement estimation using sector-shaped data. The performance of these two different strategies has been compared for the purpose of image reconstruction in REMI through TM phantom data and *in vivo* liver tissue data. Our preliminary results indicate that REMI with sector-shaped ultrasound data is feasible using current clinical equipment. We have also shown that, in TM phantoms, the elastic modulus elastograms offer an improved contrast to noise ratio (a factor of 3X), as compared to those evaluated from SE. In the two *in vivo* liver tumors, results from REMI appear to be more consistent with anatomical structure delineated by the ultrasound B-mode images, though the underlying tissue properties are not known.

In general, our results indicate that Strategy 2 outperformed Strategy 1. However, this conclusion may be influenced by the displacement tracking option and the reconstruction algorithm selected as described above. In this work, we describe the options chosen and provide justifications for our choice of the processing method. In short, this initial feasibility study is encouraging and we believe that REMI can directly work with sector-shaped ultrasound data for abdominal imaging.

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Fig. 1.

An illustration of the two image formation strategies for the proposed REMI technique. Plots on the top and bottom rows illustrate steps involved in Strategies 1 and 2, respectively. (dx, dy) denotes the lateral and axial displacement vector, while $(d\hat{x}, d\hat{y})$ denotes the horizontal and vertical displacement vector in the final Cartesian rectilinear grid. Axial and lateral directions in this paper refer to the axial and lateral direction of the original sector-shaped ultrasound data (*i.e.* the plot in the first column).

Fig. 2.

An illustration of the transformation of displacement vectors from polar coordinates to a Cartesian coordinate system in Strategy 2. In the plot, $d\hat{x}$ and $d\hat{y}$ denote the horizontal and vertical displacements in the final Cartesian coordinate system, respectively. dy and dx are the axial and lateral displacements obtained by tracking the original RF echo data. For axial displacements dy , a downward motion is positive while an upward motion is negative. For lateral displacements dx , a rightward motion is positive while a leftward motion is negative. This sign convention is consistent with motion definition in our block-matching algorithm [26].

Fig. 3.

Illustrations of the process for the calculation of elastic contrast using a strain elastogram from a TM Phantom [37]. Three selection ROI methods (a)–(c) were used. The rectangles or circles depict respective regions of interest (ROIs) in the background and the target. The target was delineated by the manually-segmented contour in orange color.

Fig. 4.

Elastographic results from the TM phantom results using two different reconstruction strategies: (a) B-mode image; (b) and (c) are vertical displacement images, (d) and (e) are vertical strain images; (f) and (g) are horizontal displacement images; (h) and (i) are horizontal strain images; and (j) and (k) are relative modulus images. Images in the left and right columns are results from Strategies 1 and 2, respectively. The white box in (a) indicates the area from which displacements were estimated and has the same size the plots (b) – (k). Arrows in (a) point to the spherical targets. Arrows in (b) and (f) point to motion tracking errors while arrows in (d) point to noise due to the aforementioned motion tracking errors.

The contour shown in (d) represents the manually-segmented target from which the CNR was calculated.

Fig. 5.

Plots of CNR values from the TM Phantom under different displacement tracking line densities: (a) CNR values of vertical strain elastograms and (b) CNR values of elastic modulus elastograms overlaid with CNR values of vertical strain elastogram. The pixel size on displacement images varied from 0.05 mm to 0.28 mm in (a) and (b).

Fig. 6.

a) B-mode image of an *in vivo* neuroendocrine liver tumor, (b) and (c) vertical displacement images (in mm) using Strategies 1 and 2, respectively, (d) and (e) vertical strain images using Strategies 1 and 2, respectively, (f) and (g) horizontal displacement images (in mm) using Strategies 1 and 2, respectively, (h) and (i) horizontal strain images using Strategies 1 and 2, respectively, and (j) and (k) relative elastic modulus elastograms using Strategies 1 and 2, respectively. The white box in (a) indicates the area from which displacements were estimated and has the same size as sizes of plots (b) – (k). The arrows in (a) point the possible contour of the neuroendocrine liver tumor, while arrows in (b), (c), (f) and (g) point

to the possible tracking errors. Results in the first and second columns are obtained from Strategies 1 and 2, respectively.

Fig. 7.

a) B-mode image of an *in vivo* HCC liver tumor, (b) and (c) vertical displacement images (in mm) using Strategies 1 and 2, respectively, (d) and (e) vertical strain elastograms using Strategies 1 and 2, respectively, (f) and (g) horizontal displacement images (in mm) using Strategies 1 and 2, respectively, (h) and (i) horizontal strain elastograms using Strategies 1 and 2, respectively, and (j) and (k) relative elastic modulus elastograms using Strategies 1 and 2, respectively. The white box in (a) indicates the area from which displacements were estimated and has the same size as sizes of plots (b) – (k). The arrows in (a) point the possible contour of the neuroendocrine liver tumor, while arrows in (b), (c), (f) and (g) point

to the possible tracking errors. Results in the first and second columns are obtained from Strategies 1 and 2, respectively.

TABLE I

A summary of elastic contrast values computed using Strategies 1 and 2 from the TM Phantom. Elastic contrast values were calculated based on Eqn. (4). S1 and S2 denote Strategies 1 and 2, respectively. Methods 1–3 corresponds to three ROI selection methods shown in Fig. 3. The EC value of SWE was based on shear wave speed measurements using a Supersonic scanner. Numbers in parentheses are relative errors as compared to the corresponding SWE measurement.

	Method #1		Method #2		Method #3		Average	
	S1	S2	S1	S2	S1	S2	S1	S2
AS	1.59	1.68	1.54	1.58	1.80	1.95	1.64 (25.4%)	1.74 (20.9%)
REMI	1.57	1.81	2.21	2.23	2.47	2.54	2.11 (4.1%)	2.17 (1.3%)
SWE	2.20							