Virtual Source Synthetic Aperture for Accurate Lateral Displacement Estimation in Ultrasound Elastography

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Abstract—Ultrasound elastography (USE) is an emerging noninvasive imaging technique in which pathological alterations can be visualized by revealing the mechanical properties of the tissue. Estimating tissue displacement in all directions is required to accurately estimate the mechanical properties. Despite capabilities of elastography techniques in estimating displacement in both axial and lateral directions, estimation of axial displacement is more accurate than lateral direction due to higher sampling frequency, higher resolution, and having a carrier signal propagating in the axial direction. Among different ultrasound imaging techniques, synthetic aperture (SA) has better lateral resolution than others, but it is not commonly used for USE due to its limitation in imaging depth of field. Virtual source synthetic aperture (VSSA) imaging is a technique to implement SA beamforming on the focused transmitted data to overcome the limitation of SA in depth of field while maintaining the same lateral resolution as SA. Besides lateral resolution, VSSA has the capability of increasing sampling frequency in the lateral direction without interpolation. In this article, we utilize VSSA to perform beamforming to enable higher resolution and sampling frequency in the lateral direction. The beamformed data are then processed using our recently published elastography technique, OVERWIND. Simulation and experimental results show substantial improvement in the estimation of lateral displacements.

Index Terms— Beamforming, regularized optimization, ultrasound elastography (USE), virtual source synthetic aperture (VSSA).

I. INTRODUCTION

ULTRASOUND elastography (USE) is a technique for detecting alterations in mechanical properties of tissue using ultrasound imaging, which is a widely available modality and offers the additional advantage of being noninvasive and low cost. As such, USE may help in early diagnosis and improves the prognosis of treatments. In recent years, USE has been utilized in several clinical applications, including ablation guidance and monitoring [1], differentiating benign thyroid nodules from malignant ones [2]–[4], and breast lesion characterization [5]–[7]. Surgical treatment of liver cancer [8]–[10], assessment of fibrosis in chronic liver diseases [11], [12], detecting prostate cancer [13], [14], differentiating abnormal lymph nodes in benign conditions [15], and brain tumor surgery [16], [17] are other relevant clinical applications of USE.

Pathological alterations are correlated with the mechanical properties of tissue, and for each material, 81 constants are required to describe the fourth-order stiffness tensor [18], [19]. Many of these parameters depend on each other in a valid stiffness tensor. Moreover, for most clinical applications, the tissue can be assumed linear elastic and isotropic, which reduces the number of parameters to two independent ones [19]. These two constants are known as the Lamé constants, or their equivalents, Young’s modulus and Poisson’s ratio.

Different methods are proposed for estimating Young’s modulus and Poisson’s ratio, which can be broadly grouped into dynamic and quasi-static elastography. Dynamic methods, such as shear wave imaging (SWI) [20] and acoustic radiation force imaging (ARFI) [21], [22], use acoustic radiation force (ARF) to stimulate displacement in tissue. Quasi-static elastography proposed in [23] uses external excitation by slowly pressing the probe against the tissue utilizing a robotic arm [24], [25] or a handheld probe (i.e., free-hand palpation) [26], [27]. Even though the induced compression is uniaxial, tissue deforms in all directions due to its incompressible property where the volume of the tissue does not change when compressed. The first step of quasi-static elastography is time-delay estimation (TDE), in which tissue deformation should be estimated and differentiated to provide the strains. In the next step, the inverse problem should be solved to estimate Young’s modulus based on strains [28], [29].

Different methods are proposed to perform TDE that can be broadly categorized as window-based, regularized optimization-based, and deep-learning approaches [30], [31]. For estimating the displacement of a sample, the window-based approaches consider a window around each sample and estimate the displacement of each window by determining a window closest in pixel values in the next frame. Several similarity metrics are proposed to compare the windows of precompressed and postcompressed tissue, such as
normalized cross correlation (NCC) of windows [32]–[34] and phase correlation in which zero crossing of phase determines displacement [35] and sum of absolute difference of windows [36]. Another class of TDE methods is regularized by an optimizing-based technique that imposes regularization between the neighboring samples [37], [38]. We have recently proposed a method called OVERWIND [39], which is a combination of window-based approaches and regularized optimization method to take advantages of both methods.

Despite the capability of OVERWIND in estimating both axial and lateral displacements, the latter is of lower quality compared with the former for three main reasons: low sampling rate, lack of carrier signal, and low resolution in the lateral direction [40], [41]. One of the most utilized techniques for increasing the data size in the lateral direction is interpolation [42], [43]. It is shown by experimental results that spline interpolation has the best performance among different techniques of interpolation [40]. In these methods, the bandwidth should be large enough to have sufficient overlap between the adjacent lines [42]. It is shown that the minimum density of A-lines for original data should be at least 2 A-line per beamwidth to have an acceptable interpolation [42]. Accordingly, not only interpolation does not change the resolution but also it cannot be implemented for high-resolution data to increase the number of samples. Besides low resolution, another disadvantage of interpolation data, especially for large factor interpolations, is decreasing the robustness of the TDE since interpolation can be a source of error [44].

Synthetic aperture (SA) imaging is used for lateral strain estimation in [45]. SA has narrow and fixed beamwidth in all fields of view in contrast to line-by-line imaging, which has narrow beamwidth in the focal zone only. Moreover, SA has capability of increasing the sampling rate in the lateral direction without interpolation, which also improves the resolution. It is shown that the accuracy of TDE increases by decreasing the beamwidth [45]. Accordingly, SA is better than line-by-line imaging for lateral elastography, with the disadvantage of lower transmission power and penetration depth, which could hinder the clinical use of SA [46], [47].

In this article, we propose to use virtual source synthetic aperture (VSSA) imaging that implements SA-based beamforming on focused transmitted signals. On the one hand, this enables us to benefit from the advantages of SA, such as high resolution and the capability to increase the sampling frequency to increase the resolution and number of A-lines. On the other hand, we can take advantage of line-by-line imaging in high penetration depth. Then, the beamformed data are fed to our recently published TDE method, OVERWIND [39] that has shown to outperform window-based and other regularized optimization-based techniques. We call the results of OVERWIND on VSSA with high sampling frequency in the lateral direction as high-frequency OVERWIND (HF OVERWIND) and compare with the results with OVERWIND on spline-based interpolated data (Inter. OVERWIND) and also with OVERWIND on VSSA with low sampling frequency in the lateral direction in which the number of A-lines is equal to the number of piezoelectrics (LF OVERWIND).

II. METHODS

Most elastography techniques such as OVERWIND requires two sets of data collected as the tissue undergoes some deformation. Let \( I_1 \) and \( I_2 \) of size \((m, n)\) be the beamformed RF data, where \(m\) and \(n\) are depth and width of the imaged tissue. The goal of TDE is estimating the displacement field between these two data sets. In this section, we first briefly review our recently developed USE method, OVERWIND [39], and then present the beamforming technique to increase the number of lines and resolution in the lateral direction to help OVERWIND in accurately estimating displacements.

A. Overwind: tOtal Variation Regularization and Window-Based TDE

The displacement estimation in OVERWIND comprises two steps for increasing the capabilities of the technique in estimating large deformations. In the first step, an integer estimation of the displacement is calculated using dynamic programming (DP), which is a recursive optimization-based method for image registration. In this method, we consider a range of displacements for each sample and optimize the cost function that incorporates similarity of RF samples and displacement continuity to estimate integer displacement of RF samples [48]. In the second step, the subsample displacements are calculated by minimizing the following cost function:

\[
C(A_{l_{1,1}}, \ldots, A_{l_{m,n}}) = \sum_{j=1}^{n} \sum_{i=1}^{m} \frac{1}{L} \sum_{r=1}^{L} \left[ \frac{1}{2} \left( I_1(i + k, j + r) - I_2(\cdot) - A_{l_{i,j}} I'_{2a}(\cdot) \right)^2 \right. \\
+ a_1 \delta_1(a_{i,j} + A_{l_{i,j}} - A_{l_{i,j} - 1}) \left. + a_2 \delta_2(a_{i,j} - A_{l_{i,j} - 1}) \right] + \beta_1 \delta_3(l_{i,j} + A_{l_{i,j}} - l_{i,j - 1}) + \beta_2 \delta_4(l_{i,j} - l_{i,j - 1} - A_{l_{i,j} - 1})
\]

where \(i\) and \(j\) are indices of RF samples in the region of interest and the symbols \(i + k \) and \(j + r\) represent indices of RF samples inside the window that is considered around each sample. \(a_{i,j}, A_{l_{i,j}}\) and \(l_{i,j}, A_{l_{i,j}}\) represent the integer and subsample displacement of \((i, j)\) in axial and lateral directions, respectively. \(I_2(\cdot)\) represent \(I_2(i + k + a_{i,j}, j + r + l_{i,j})\) and \(I'_{2a}(\cdot)\) and \(I'_{2b}(\cdot)\) are derivatives of \(I_2\) in the axial and lateral directions, respectively. \(\delta_3(s) = 2\lambda_s(x^2 + s^2)^{1/2}\) is an approximate of norm L1 for regularization, which allows sharp transitions where \(\lambda_s\) is a scaling parameter. Finally, \(a_1, a_2, \beta_1,\) and \(\beta_2\) are regularization parameters to be tuned. These four parameters can be related to each other, as explained in Section IV.

OVERWIND considers both displacements in axial and lateral directions, but the estimation in the former direction is more accurate since, among other reasons, ultrasound data usually have less samples in the lateral direction compared to the axial direction. One of the most common techniques to cope with this issue is interpolating data in the lateral
direction. Not only it does not change the resolution but also its performance can deteriorate for the high-resolution data sets since the A-lines do not have high overlap with each other in the high-resolution data [49], [50]. Another disadvantage of interpolation is low robustness for complex interpolation techniques.

In this article, we propose to use VSSA imaging mode for USE, which has the ability to increase sampling frequency in the lateral direction as much as axial direction and also has high resolution in the lateral direction while allowing high penetration. In Section II-B, we describe SA, line-by-line imaging, and then show how VSSA can benefit to relax two main limitations for lateral displacement estimation in USE.

**B. SA: Synthetic Aperture**

In SA, a single element transmits a wave through the tissue, as shown in Fig. 1(a), and all elements record reflections. Each element generates an image of tissue [the gray area of Fig. 1(a)] by focusing the received beam at any point according to the expression

$$t_p(i,j) = \frac{\sqrt{(x_p-x_i)^2 + (z_p)^2} + \sqrt{(x_p-x_j)^2 + (z_p)^2}}{c}$$  \hspace{1cm} (1)

where $c$ is the speed of sound in soft tissue and $i$ and $j$ are the transmitter and receiver elements symbols. $x_i$, $x_j$, and $x_p$ are the horizontal positions of the transmitter $i$, receiver $j$, and point $p$ where the beam is focused and $z_p$ is the depth of point $p$ by assuming that the probe is at zero depth. During each transmission, all receivers in the aperture focus the received beam at all points of the aperture and summation of these data for all receivers generate a low-resolution image. The next element of the array transmits and the previously described operation is repeated to generate another low-resolution image. By repeating the experiment for all piezoelectrics as transmitter and adding up all low-resolution images, the final image is generated as per the following expression:

$$y_p = \sum_{i=1}^{e} \sum_{j=1}^{e} t_p(i,j)$$  \hspace{1cm} (2)

where $e$ is the total number of elements in the transducer array. The main disadvantage of this technique for USE is the limitation in imaging deep areas since the emitted signal from one piezoelectric does not have enough power to penetrate deep areas.

**C. Line-by-Line Imaging**

In this imaging technique, a group of elements (i.e., transmission aperture) transmits the beam to increase the penetration of signal to image deeper areas. The transmitted beam focuses at a single point during each transmission. The data received at different channels are processed to generate one line of the US image. Fig. 1(b) shows the pattern of transmission by dashed red lines, while the area that is imaged in each transmission is highlighted by gray. In this technique, the lateral resolution at the focal depth is high and close to the resolution of the SA imaging. Further away from this point, the resolution decreases. Moreover, the number of lines is limited to the number of elements (without interpolation).

**D. VSSA: Virtual Source Synthetic Aperture**

This imaging technique benefits from both SA and line-by-line imaging and has the ability of increasing sampling frequency and resolution in lateral direction in all imaged area while penetrating to deep fields that are essential for USE. Similar to line-by-line imaging, a group of elements transmits the beam by focusing at a single point [51], [52]. Since the beam at the focal point is very narrow, we can assume the focal point as a virtual source that transmits the beam similar to SA, as shown in Fig. 1(c). Then, each receiver focuses the received data at any point inside the aperture according to the following expression [53]:

$$z_f = \frac{\sqrt{(x_p-x_f)^2 + (z_f-z_p)^2} + \sqrt{(x_f-x_p)^2 + z_f^2}}{c}$$  \hspace{1cm} (3)

where $c$ is the speed of sound in soft tissue, $x_p$, $x_f$, $z_p$, and $z_f$ are the positions of the focal point $f$, and $p$ is the
Fig. 2. Estimated lateral displacement with LF OVERWIND, Inter. OVERWIND, and HF OVERWIND for simulation data are shown in (b)–(d), respectively. The second row shows the corresponding strains. The red and blue rectangles in (e) are considered as target and background areas for CNR calculation. The horizontal white and green vertical lines are also used for plotting the ESF of Fig. 3. (a) and (e) Ground truth. (b) and (f) LF OVERWIND. (c) and (g) Inter. OVERWIND. (d) and (h) HF OVERWIND.

Fig. 3. ESF of the lateral strain in (a) horizontal and (b) vertical lines.

Similar to line-by-line imaging, the number of A-lines is usually equal to the number of elements in VSSA, and interpolation is the most commonly used technique for increasing the sampling frequency in the lateral direction for elastography purposes. However, for the VSSA, the received data can be focused at any point inside the aperture [highlighted by gray in Fig. 1(c)]. To increase the sampling frequency, we consider a grid consisting of nodes with the same spatial distance of nodes in the axial and lateral directions as \( p_d = (c/2f_s) \). Each receiver element generates an image on that grid, as shown in Fig. 1(c). Therefore, we can increase the number of data and resolution in the lateral direction without interpolation.

### E. Data Acquisition and Comparison Metrics

In this section, the data that are utilized in different experiments of this article are described, and then, the results of HF OVERWIND are compared with Inter. OVERWIND and also LF OVERWIND in which a number of data in lateral direction are equal to number of piezoelectrics. In Section III, the CNR metric is used to provide a quantitative value for assessing the proposed method [54]

\[
\text{CNR} = 20 \log_{10} \left( \frac{2(\bar{s}_t - \bar{s}_b)}{\sigma_t^2 + \sigma_b^2} \right) \tag{5}
\]

where \( \bar{s}_t \) and \( \bar{s}_b \) are the spatial strain averages of the target and background, respectively, and \( \sigma_t^2 \) and \( \sigma_b^2 \) are the spatial strain variances of the target and background, respectively [19]. For the simulation results where we know the ground truth, we use root-mean-square error (RMSE), mean of estimation error (ME), and variance of estimation error (VE) as other metrics according to

\[
\text{RMSE} = 100 \times \sqrt{\frac{\sum_{i=1}^{m} \sum_{j=1}^{n} (S_e(i, j) - S_g(i, j))^2}{m \times n}}
\]

\[
\text{ME} = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} S_e(i, j) - S_g(i, j)}{m \times n}
\]

\[
\text{VE} = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} (S_e(i, j) - S_g(i, j))^2}{m \times n} - \text{ME}^2 \tag{6}
\]
where \( m \) and \( n \) are size of estimated strains and \( S_e \) and \( S_g \) are estimated and ground truth strains, respectively.

For estimating the axial strain, the displacement field should be differentiated. To reduce the impact of noise during differentiating, it is common to use least square estimation (LSQ) for strain estimating. For estimating the strain at each sample, a few neighboring samples in a window of size \( \rho \) are considered and a line is fitted to their displacements. The tangent of the line is considered as the strain for the middle sample. Considering more data points for least square makes the strain smooth at the cost of losing resolution. Throughout this article, the size of LSQ window is 5% of total data size.

1) Simulation Data: A simulated phantom is generated by utilizing the Field II ultrasound simulation software [55], [56] by randomly distributing slightly more than ten scatterers per resolution cell to satisfy the Rayleigh scattering regime.

The simulated phantom consists of a homogeneous region with Young’s modulus of 4 kPa and one cylindrical inclusion with Young’s modulus of 40 kPa. For compressing the phantom and computing its ground-truth displacement, finite-element method (FEM)-based deformations are computed using the ABAQUS software package (Johnston, RI, USA) with triangular mesh sizes of 0.05 mm². The probe consists of 128 elements with a pitch of 0.15 mm. The center frequency is 7 MHz, whereas the sampling rate is 100 MHz. The lateral sampling frequency in HF OVERWIND is 19 times higher than LF OVERWIND. Therefore, the data are interpolated by a factor of 19 and using a cubic spline method for Inter. OVERWIND so that Inter. OVERWIND and HF OVERWIND have the same number of samples.

2) Phantom Data: The phantom data are acquired from a tissue-mimicking breast phantom (059 tissue-mimicking breast phantom, CIRS tissue simulation, and phantom technology, Norfolk, VA, USA) using an E-Cube R12 ultrasound machine (Alpinion, Bothell, WA, USA) with an L3-12H probe at the center frequency of 8 MHz and the sampling frequency of 40 MHz. The lateral sampling frequency in HF OVERWIND is eight times higher than LF OVERWIND, and therefore, the data are interpolated by a factor of 8 using the cubic spline method for Inter. OVERWIND.

III. RESULTS

A. Simulation Results

Fig. 2 shows the lateral displacement and strain for LF OVERWIND, Inter. OVERWIND, and HF OVERWIND. It is clear that elastography on data sampled at a higher rate significantly improves the estimations. As anticipated, the interpolation decreases the variance of estimation significantly at the expense of oversmoothing compared to low sampled data.
Fig. 6. Results on a tissue-mimicking phantom. Estimated lateral displacement with LF OVERWIND, Inter. OVERWIND and HF OVERWIND are shown in (b)–(d), respectively. The second row shows the corresponding strains. The red and blue rectangles in (a) are considered as target and background areas for CNR calculation. (a) B-MODE. (b) and (e) LF OVERWIND. (c) and (f) Inter. OVERWIND. (d) and (g) HF OVERWIND.

**TABLE I**

| QUANTITATIVE COMPARISON OF LATERAL STRAIN ESTIMATION ON SIMULATED PHANTOM |
|-----------------------------|-----------------------------|
| **LF OVERWIND** | **Inter. OVERWIND** | **HF OVERWIND** |
| ME | $-1.1 \times 10^{-4}$ | $1.6 \times 10^{-3}$ | $4.33 \times 10^{-4}$ |
| VE | $9.77 \times 10^{-6}$ | $2.18 \times 10^{-6}$ | $6.21 \times 10^{-7}$ |
| RMSE | 85.04% | 56.73% | 23.09% |
| CNR | 0.37 | -1.49 | 21.70 |

Fig. 6 also shows the axial displacement and strain for laterally low sampled data, interpolated data, and laterally high sampled data. It is inevitable that correct lateral estimation leads to slightly improved axial estimations. Table II and Fig. 5 show the marginal improvement of axial strain.

**B. Phantom Results**

Estimated lateral displacement and strain for experimental phantom are shown in Fig. 6. Similar to the simulation study, the lateral estimation by spline interpolation is oversmoothed and HF OVERWIND outperforms the previous methods. Fig. 7 shows the axial displacements and strains, and it illustrates better performance of HF OVERWIND over both LF OVERWIND and Inter. OVERWIND. The reported CNR values in Table III also show improvement in both lateral and axial estimations by HF OVERWIND.

**IV. DISCUSSION**

In this article, we proposed to use VSSA as an advanced beamforming technique for TDE in OVERWIND. In this imaging technique, multiple piezoelectrics participate in the transmission, which improves the beam strength in deep regions. The focused region of the beam can be considered as a virtual element that transmits a beam in tissue. As such, the imaging procedure becomes closer to the operation of the
Fig. 7. Results on a tissue-mimicking phantom. Estimated axial displacement with LF OVERWIND, Inter. OVERWIND, and HF OVERWIND are shown in (a)–(c), respectively. The second row shows the corresponding strains. (a) and (d) LF OVERWIND. (b) and (e) Inter. OVERWIND. (c) and (f) HF OVERWIND.

Fig. 8. Discontinuity of the VSSA imaging in the focal depth.

SA and received data can be beamformed similar to SA. In this imaging mode, the sampling frequency in the lateral direction can be increased as much as the sampling frequency in the axial direction to increase the resolution and addresses two of the major limitations in estimation lateral displacements. Meanwhile, VSSA has fixed and narrow beamwidth in all imaging field, which results in accurate and high-resolution displacement estimation.

VSSA assumes the focal point as a beam source that transmits the signal and conducts beamforming according to (3). The ± term in (3) divides the imaging area into the top and bottom regions above and below the virtual source resulting in a discontinuity at the focal depth, as shown in Fig. 8. This discontinuity is a source of error for USE. Therefore, the focal point should be established in an area outside the region of interest and the corresponding data should be cropped before elastography to avoid this discontinuity.

In addition to the advantages associated with HF OVERWIND with respect to higher accuracy and increased resolution in its estimation, tuning the parameters in HF OVERWIND is much easier than LF OVERWIND. The OVERWIND cost function has four regularization parameters, namely $\alpha_1$, $\alpha_2$, $\beta_1$, and $\beta_2$. The parameters $\alpha_1$, and $\beta_1$ regularize the displacements of two neighboring samples in the same A-line in axial and lateral directions, whereas $\alpha_2$ and $\beta_2$ regularize displacements of two neighbor samples at the same depth and neighbor A-line, respectively. As a rule of thumb, by assuming the Poisson’s ratio of biological tissues close to 0.5, lateral displacements of two samples are half of axial displacements, and therefore, $\beta_1$ and $\beta_2$ can be adjusted as $\beta_1 = 0.5 \times \alpha_1$ and $\beta_2 = 0.5 \times \alpha_2$, to reduce the number of parameters to two. In HF OVERWIND, the sample size in axial and lateral directions is equal. Therefore, $\alpha_2$ can be set equal to $\alpha_1$ to reduce the number of parameters to one parameter.

The VSSA yielding high sampling frequency and high resolution in the lateral direction can be utilized with all elastography techniques, and it significantly improves the results. For window-based techniques such as NCC, it is important to note that they are slow and computationally expensive techniques even for data with a low sampling frequency in the lateral direction. In window-based techniques, the running time has a linear relationship with image size, which is a disadvantage of these techniques for VSSA with high sampling frequency in the lateral direction. The data with high sampling frequency can also be utilized for other regularized optimization-based elastography techniques. However, oversmoothness is a challenging issue for regularized optimization-based techniques due to a low resolution and also smaller deformation in the lateral direction, and it is shown in [39] that OVERWIND has a better capability in estimation the sharp transitions.

V. CONCLUSION

Accurate estimation of the tissue mechanical parameters requires accurate strain estimation in all directions. Although elastography techniques estimate displacements in both axial
and lateral directions, estimation in the axial direction is more accurate than in the lateral direction due to high sampling frequency, improved axial resolution, and a carrier signal propagating in the axial direction. In this article, we proposed to use the VSSA imaging mode to benefit from advantages of both SA and line-by-line imaging in a high resolution with a high number of A-lines and penetration depth. The beamformed data are fed to our recently developed TDE method, OVERWIND. The results exhibit significant improvement compared with interpolating data in the lateral direction as one of the commonly used techniques in estimating lateral strain.

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