Published in final edited form as:

IEEE Trans Ultrason Ferroelectr Freq Control. 2011 April ; 58(4): 838–843. doi:10.1109/TUFFC.2011.1876.

An Autocorrelation-Based Method for Improvement of Sub-Pixel Displacement Estimation in Ultrasound Strain Imaging

Seungsoo Kim[Student Member, IEEE] and **Salavat R. Aglyamov**[Member, IEEE]
University of Texas, Biomedical Engineering Department, Austin, TX

Suhyun Park

GE Global Research, Ultrasound and Biomedical Imaging Laboratory, Niskayuna, NY

Matthew O'Donnell[Fellow, IEEE]

University of Washington, Bioengineering Department, Seattle, WA

Stanislav Y. Emelianov[Member, IEEE]

University of Texas, Biomedical Engineering Department, Austin, TX

Abstract

In ultrasound strain and elasticity imaging, an accurate and cost-effective sub-pixel displacement estimator is required because strain/elasticity imaging quality relies on the displacement SNR, which can often be higher if more computational resources are provided. In this paper, we introduce an autocorrelation-based method to cost-effectively improve sub-pixel displacement estimation quality. To quantitatively evaluate the performance of the autocorrelation method, simulated and tissue-mimicking phantom experiments were performed. The computational cost of the autocorrelation method is also discussed. The results of our study suggest the autocorrelation method can be used for a real-time elasticity imaging system.

I. Introduction

Ultrasound strain imaging has emerged as a tool for a wide range of biomedical applications. For high-quality strain images, an accurate motion tracking method is required because strain tensor maps (i.e., spatial derivatives of displacements) and elasticity images (i.e., processed strain images removing the influence of mechanical boundary conditions [1]) are greatly dependent on the quality of displacement vector estimates. Computational costs must also be considered to assess the feasibility of implementing the technique in a real-time system.

The nature of sampled signals has raised the importance of sub-pixel displacement estimations which often dominate the SNR of displacement vectors. Many approaches to estimate sub-pixel displacements in ultrasound strain imaging have already been developed and reported [2]–[8]. The most straightforward approach to achieve sub-pixel precision is to interpolate the sampled signal and then to estimate displacements in terms of interpolated integer pixels [3]. In this case, however, computational costs are significantly increased by the interpolation factor and sub-pixel precision may not be enough. A spline-based algorithm [7] can be used to solve these problems but the method is still computationally expensive.

Another approach to estimate sub-pixel displacements is to interpolate pattern matching functions such as the normalized cross-correlation (NCC), sum of squared differences (SSD), and sum of absolute differences (SAD) [2], [4]–[6]. Using the linear phase property of the NCC function, the best pattern matching position (i.e., displacement) between two RF signals with sub-pixel precision can be obtained [4], [5]. However, to utilize phase information, the complex NCC function must be computed, and therefore, computational costs increase compared with curve-fit methods of pattern matching functions, such as either parabola or cosine fit, with either NCC, SSD, or SAD. In these methods, bias error degrades displacement SNR [2]. Furthermore, for lateral displacement estimation, interpolating sparsely sampled lateral data was suggested to improve displacement SNR [8], and synthetic lateral phase was introduced to utilize the phase zero-crossing method in the lateral direction as well [6].

In this paper, we introduce an autocorrelation-based speckle-tracking error removal method to improve the performance of sub-pixel displacement estimation without significantly increasing the computational burden. The main goal is to remove sub-pixel estimation errors caused purely by curve-fitting interpolation (e.g., parabola, cosine, etc.). In our method, referred to as autocorrelation, the error can be estimated using the displacement between two identical frames. The autocorrelation method was quantitatively evaluated in strain imaging experiments using both simulated and tissue-mimicking phantom data.

II. Approach

Although we demonstrate the autocorrelation method on only parabolic interpolation of the NCC function, all other techniques based on curve-fitting of pattern matching functions would have the same source of estimation errors and can be improved by the autocorrelation method.

In 1-D parabolic interpolation, the sample corresponding to the peak of the NCC function and two samples neighboring the peak are used to determine the position of the peak with sub-pixel precision. The sub-pixel displacement, δ , obtained using 1-D parabolic interpolation is

$$\delta = \frac{R(l_{\max} - 1) - R(l_{\max} + 1)}{2(R(l_{\max} - 1) - 2R(l_{\max}) + R(l_{\max} + 1))}, \quad (1)$$

where $R(l)$ represents the correlation coefficient at correlation lag l , and $l_{\max}$ is the correlation lag where the correlation coefficient is the maximum.

Because the parabolic fit is not necessarily correct for a continuous NCC function, error is introduced [2]. This error depends not only on the sampling rate, but also on the details of the correlation function at a particular position. On average, the shape of the NCC function is determined by the point spread function (PSF) of the imaging system. At an individual pixel, however, the details of the scatterer distribution in that pixel modulate this average shape. The easiest way to reduce errors is to increase the data sampling rate so that the influence of parabolic interpolation errors can be minimized. However, increased data sampling rates lead to significant increases in computational cost.

Because sub-pixel displacement estimation using parabolic interpolation is imperfect, estimated displacements between identical frames are nonzero even though there shouldn't be any motion. It can be assumed the nonzero displacements obtained using autocorrelation (i.e., correlation between identical frames) are sub-pixel displacement estimation errors related to the intrinsic curve-fit method and speckle statistics. Therefore, displacement

estimation errors can be effectively removed by subtracting autocorrelation-based displacements from the displacements obtained using cross-correlation of two neighboring ultra-sound frames captured during tissue deformation. Fig. 1(a) illustrates a block diagram of the autocorrelation-based method. Using the same displacement estimator, the displacement between two neighboring frames (i.e., cross-correlation between reference and displaced frames) and the same frame (i.e., autocorrelation of the reference frame) are computed simultaneously. From the autocorrelation results, error patterns related to the intrinsic curve-fit method and speckle statistics are obtained. Then, by subtracting autocorrelation-based displacements from those obtained using cross-correlation, displacement errors produced by inaccurate curve-fit interpolation during sub-pixel displacement estimation are largely eliminated. Although in our study only the reference frame was used for the autocorrelation, it is easily expanded to include both reference and displaced frames [Fig. 1(b)].

III. Materials and Methods

A. Simulated Phantom

A phantom with a single, hard inclusion embedded into a homogenous medium was simulated. The 10-mm diameter circular inclusion had 50 times more randomly distributed scatterers than the background medium for contrast in ultrasound images. For contrast in elasticity images, the inclusion was twice as hard as the background material. To model the displacement and deformation of the phantom, a 2-D analytical solution for an incompressible, uniformly deformed body with cylindrical inclusion was used [1]. Ultrasound modeling was based on far-field approximated linear acoustic wave propagation. Each element of the transducer (128-element linear array operating at 5 MHz) was assumed to be a point source and a detector with the directivity of a 300- μ m wide acoustic radiator. The spatial impulse response of the transducer was modeled as a three-cycle sinusoid with a Hanning-weighted envelope corresponding to a 60% fractional bandwidth. The backscattered ultrasound signal was captured using a 40 MHz sampling frequency [9].

B. Tissue-Mimicking Phantom and Data Acquisition

Fabrication of the tissue-mimicking phantom closely followed the procedure described elsewhere [10]. Briefly, the background of the 40 $\times$ 50 $\times$ 60-mm rectangular cuboid phantom was made out of 8% polyvinyl alcohol (PVA) solution and 1% 40- μ m silica particles acting as ultrasound scatterers. For the inclusion, 10% PVA and 2% silica were mixed to fabricate the hyperechoic inclusion approximately 2.5 times harder than the background. The diameter of the cylindrical inclusion was 10-mm. During fabrication, the inclusion was positioned in the middle of the 50-mm by 60-mm face such that the circular cross-section of the inclusion was imaged.

RF data (128 beams, 2592 samples) were recorded using a Sonic RP ultrasound system (Ultrasonix Medical Corporation, Vancouver, BC, Canada) with 64 transmit channels and 32 receive channels for each ultrasound beam or scanline. A 128-element, 0.3048-mm pitch linear array transducer (114-5/38, Prosonic Corporation, Gyeongju, Korea) with a 5 MHz center frequency and 60% fractional bandwidth was used. Surface deformations up to 2.7% axial strain were applied in 0.3% increments using the surface of the transducer array itself. The RF data sampling frequency was 40 MHz.

C. Processing Algorithm and SNR

To track in-plane motion between two frames, a 2-D region was searched using a 2-D kernel. The kernel size was 0.64-mm (33 samples at 40 MHz) axially and 0.91-mm (3 out of 128 scanlines) laterally. For integer-pixel displacement estimations, the NCC was

calculated. Then, sub-pixel displacements were estimated using parabolic interpolation of the NCC function in both axial and lateral directions, separately. To evaluate the effects of the developed autocorrelation-based method only, no post-processing, such as spatial filtering, was applied. For the axial displacement, a phase-based sub-pixel displacement estimation method, called phase zero-crossing [4], was used to compare with the autocorrelation method. For the lateral displacement, linear interpolation (2-, 4-, and 8-fold) of lateral samples was performed and displacement estimation followed. The kernel size was kept the same, at 0.91-mm laterally (i.e., 6 out of 256, 12 out of 512, and 24 out of 1024 scanlines).

Several regions of interest (ROIs) were used to compute the SNRs of axial and lateral displacements, as shown in Fig. 2. Three vertically spread ROIs were used to analyze axial displacements, and three horizontally spread ROIs were used to analyze lateral displacements. The SNR was computed using

$$\text{SNR} = 20 \cdot \log_{10} \left(\frac{\sum_{\text{ROI}} \text{ref}(x, y) / N}{\sqrt{[\sum_{\text{ROI}} (\text{ref}(x, y) - \text{est}(x, y))^2] / N}} \right), \quad (2)$$

where $\text{ref}(x, y)$ and $\text{est}(x, y)$ are reference displacement and estimated displacement at the (x, y) position. In this equation, x and y are lateral and axial coordinates, respectively, where the axis of the ultrasound beam is directed along the y -axis (Fig. 2). In the tissue-mimicking phantom study, the linear fit within a 2-mm window of estimated displacement obtained by the phase zero-crossing method was used for the axial reference displacement. For the lateral reference displacement, the linear-fit within a 5-mm window of estimated displacement obtained by the parabolic interpolation method using 1024 interpolated scan lines was used. The noise is defined as the difference between reference and estimated displacements.

Five different data sets for each applied strain were used to calculate SNR statistics. For 0.3% applied strain, for example, the displacements between frames 1 and 2, 2 and 3, 3 and 4, 4 and 5, and 5 and 6 were analyzed.

D. Computational Complexity

In correlation-based speckle tracking, the computational load is dominated by computation of the NCC function. The normalized computational cost, C_{NCC} , for the normalized cross-correlation method is:

$$C_{\text{NCC}} = [(K_A \times K_L) \times 3] \times (S_A \times S_L), \quad (3)$$

where K_A is the axial kernel size, K_L is the lateral kernel size, S_A is the axial search range, and S_L is the lateral search range. Here, we consider only the number of multiplications because multiplications dominate computational complexity. The computational cost for a complex normalized cross-correlation is four times more than C_{NCC} because of complex multiplications.

In contrast, to obtain either axial or lateral sub-pixel displacement estimation errors, the autocorrelation-based method requires only two more correlation coefficients, which are either $R(-1, 0)$ and $R(1, 0)$ or $R(0, -1)$ and $R(0, 1)$ where $R(x, y)$ represents the correlation coefficient at axial lag x and lateral lag y . Therefore, the normalized computational cost of the autocorrelation-based method can be derived as

$$\begin{aligned}
C_{AC} &= C_{NCC} + [(K_A \times K_L) \times 3] \times 2 \\
&= [(K_A \times K_L) \times 3] \times (S_A \times S_L + 2).
\end{aligned} \tag{4}$$

Note that we consider only one direction (i.e., either axial or lateral direction) for computing the computational cost of the autocorrelation method.

IV. Results and Discussion

A. Axial Displacements

As expected, the SNR of the axial displacement for the autocorrelation method (i.e., parabolic interpolation of NCC function minus parabolic interpolation of autocorrelation function) is higher than that for the conventional cross-correlation method (i.e., parabolic interpolation of NCC function) for all deformation levels [Fig. 3(a) for simulated and Fig. 3(b) for tissue-mimicking phantom]. This improvement was more pronounced at low deformation; this is expected because sub-pixel interpolation error is nearly the same for all deformations whereas the displacement is small for low deformation. In other words, sub-pixel displacement estimation errors play a more significant role for low deformations and, consequently, the autocorrelation method has greater impact.

The SNR of the autocorrelation method, however, is still lower than that of the phase-based approach. This is because the phase of the matching function (i.e., normalized complex cross-correlation) can be modeled as a nearly perfect linear function, whereas the magnitude of the matching function (i.e., normalized cross-correlation) is not perfectly matched with a parabolic function. Although the autocorrelation method could not exceed the limit of the parabola fit, and therefore, could not reach the SNR of the phase-based method, its additional computational cost is only about 22% that of the conventional curve-fitting method. Furthermore, about 77% less computational load is required to implement the autocorrelation method compared with the phase zero-crossing method [Fig. 3(c)].

For the phase zero-crossing method, some tradeoff between SNR and computational cost must be considered. Because computational cost is highly dependent on the search range (i.e., number of samples in the search window), skipping samples in the search window can decrease computational cost and the decrease in SNR from skipping samples is relatively small because of the strength of the linear fit to phase.

B. Lateral Displacements

Because lateral samples are sparser than axial samples, the sub-pixel displacement estimation is critically important to the quality of lateral displacement estimation vectors. By applying the autocorrelation-based method, lateral displacement estimation errors were dramatically decreased. For 0.3% surface applied deformation of both simulated and tissue-mimicking phantoms, the autocorrelation-based method increases lateral displacement SNR by more than 12 dB compared with the conventional cross-correlation method [Fig. 3(d) and Fig. 3(e), respectively]. The performance of the autocorrelation method for lateral displacements is nearly the same for the simulated phantom and even better for the tissue-mimicking phantom compared with the conventional method using 8-fold interpolated data (i.e., 1024 scanlines). The conventional method using 8-fold interpolated data requires about 64 times more computational resources, keeping the same size of kernel and search range, than the original 128 scanline data [Fig. 3(f)].

V. Conclusions

The results of our study suggest the autocorrelation-based method can be used for cost-effective real-time strain imaging. In particular, the autocorrelation method can significantly help in lateral displacement estimation.

Acknowledgments

This work was supported in part by National Institutes of Health under Grant EB 004963 and HL 091609.

References

- [1]. Skovoroda AR, Emelianov SY, o'Donnell M. Tissue elasticity reconstruction based on ultrasonic displacement and strain images. *IEEE Trans. Ultrason. Ferroelectr. Freq. Control.* 1995; 42(no. 4):747–765.
- [2]. Cespedes I, Huang Y, Ophir J, Spratt S. Methods for estimation of subsample time delays of digitized echo signals. *Ultrason. Imaging.* 1995; 17(no. 2):142–171. [PubMed: 7571208]
- [3]. Konofagou E, Ophir J. A new elastographic method for estimation and imaging of lateral displacements, lateral strains, corrected axial strains and Poisson's ratios in tissues. *Ultrasound Med. Biol.* 1998; 24(no. 8):1183–1199. [PubMed: 9833588]
- [4]. Lubinski MA, Emelianov SY, O'Donnell M. Speckle tracking methods for ultrasonic elasticity imaging using short-time correlation. *IEEE Trans. Ultrason. Ferroelectr. Freq. Control.* 1999; 46(no. 1):82–96. [PubMed: 18238401]
- [5]. Pesavento A, Perrey C, Krueger M, Ermert H. A time-efficient and accurate strain estimation concept for ultrasonic elastography using iterative phase zero estimation. *IEEE Trans. Ultrason. Ferroelectr. Freq. Control.* 1999; 46(no. 5):1057–1067. [PubMed: 18244299]
- [6]. Chen X, Zohdy MJ, Emelianov SY, O'Donnell M. Lateral speckle tracking using synthetic lateral phase. *IEEE Trans. Ultrason. Ferroelectr. Freq. Control.* 2004; 51(no. 5):540–550. [PubMed: 15217232]
- [7]. Viola F, Walker WF. A spline-based algorithm for continuous time-delay estimation using sampled data. *IEEE Trans. Ultrason. Ferroelectr. Freq. Control.* 2005; 52(no. 1):80–93. [PubMed: 15742564]
- [8]. Luo J, Konofagou EE. Effects of various parameters on lateral displacement estimation in ultrasound elastography. *Ultrasound Med. Biol.* 2009; 35(no. 8):1352–1366. [PubMed: 19525061]
- [9]. Park S, Aglyamov SR, Scott WG, Emelianov SY. strain imaging using conventional and ultrafast ultrasound imaging: Numerical analysis. *IEEE Trans. Ultrason. Ferroelectr. Freq. Control.* 2007; 54(no. 5):987–995. [PubMed: 17523563]
- [10]. Park S, Aglyamov SR, Emelianov SY. Elasticity imaging using conventional and high-frame rate ultrasound imaging: Experimental study. *IEEE Trans. Ultrason. Ferroelectr. Freq. Control.* 2007; 54(no. 11):2246–2256. [PubMed: 18051159]

Fig. 1.

Block diagram of the autocorrelation-based method for improved sub-pixel displacement estimation. The autocorrelation output denotes displacement estimation errors related to the intrinsic method and speckle statistics. Clearly, outputs of the autocorrelation-based method do not have high-frequency noise caused by sub-pixel estimation errors. The autocorrelation approach based on (a) reference frame and (b) both reference and displaced frames.

Fig. 2. Ultrasound images of (a) simulated phantom and (b) the tissue-mimicking phantom. Regions of interest (ROIs) for axial and lateral displacements are outlined by dotted and dashed lines, respectively.

Fig. 3.

Axial and lateral displacement SNR for 0.3% to 1.5% axial deformations in 0.3% increments: (a) and (d) are for axial and lateral displacement SNR from the simulation; (b) and (e) are from the tissue-mimicking phantom; (c) and (f) indicate computational cost comparisons for axial and lateral displacement estimators, respectively.