An Adaptive Strain Estimator for Elastography

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Abstract—Elastography is based on the estimation of strain due to applied tissue compression. In conventional elastography, strain is computed from the gradient of the displacement estimates between gated pre- and postcompression echo signals. Gradient-based estimation methods are known to be susceptible to noise. In elastography, in addition to the electronic noise, a principal source of estimation error is the decorrelation of the echo signal as a result of tissue compression (decorrelation noise).

Temporal stretching of postcompression signals previously was shown to reduce the decorrelation noise. In this paper, we introduce a novel estimator that uses the stretch factor itself as an estimator of the strain. It uses an iterative algorithm that adaptively maximizes the correlation between the pre- and postcompression echo signals by appropriately stretching the latter. We investigate the performance of this adaptive strain estimator using simulated and experimental data. The estimator has exhibited a vastly superior performance compared with the conventional gradient-based estimator.

I. INTRODUCTION

Over the past several years, ultrasonic imaging methods based on tissue elasticity have gained significance for diagnosis of disease [1]-[7]. These methods fall into two main groups: methods where a low frequency vibration is applied to the tissue and the resulting behavior is inspected [1]-[4], [7], and methods where a compression is applied to the tissue and the resulting strain is estimated [5], [6]. Among the first group of techniques, in sonoelasticity imaging [2], [3], the vibration amplitude pattern of the shear waves in the tissue under investigation is detected and a corresponding color image (similar to color Doppler display) is superimposed on the conventional grayscale image. A theory of sonoelasticity imaging was developed [8] and in vitro results on excised human prostate were promising [9]. Among the techniques based on the estimation of tissue strain, elastography [5] is based on estimating the tissue strain using a correlation algorithm, whereas another elasticity imaging technique is based on estimating such strain using the phase information [6]. In elastography, the local tissue displacements are estimated from the time delays between gated pre- and postcompression echo signals, whose axial gradient is then computed to estimate the local strain.

In elastography, the quality of time delay estimation affects the quality of strain estimation and, hence, that of the elastogram. Conventional elastography [5] is a gradient-based method, where the strain is estimated from the first difference of the time delays between two successive signal segments. The gradient operation introduces a significant amount of noise into the strain estimates, especially for small correlation window sizes and/or large overlap between the successive correlation windows. However, to increase resolution, using a small correlation window size is desirable; moreover, to track rapid changes in elasticity, large window overlap may be used. In this article, we propose a novel estimator based on temporal stretching [10]-[12] of the postcompression echo signals. In an earlier paper [12], we demonstrated that temporal signal stretching results in a much improved correlation between the signals. The natural extension of that study was to use the stretching factor itself as the estimator. For the new estimator, we iteratively vary the stretching factor that is applied to the postcompression signal until the correlation coefficient function between the pre- and the postcompression signal is maximized. Because no gradient operation is associated with this new estimator, it does not suffer from the noise amplification associated with gradient methods. We have thoroughly investigated the estimator using simulated data from 2-D finite element modeling (FEM) to gain a good understanding of its performance. The results were corroborated using experimental data.

II. THEORY

A. The Method

In a homogeneous target, the zero-mean pre- and postcompression echo-signals can be modeled by:

\[ r_1(t) = s_1(t) + n_1(t) = s(t) * p(t) + n_1(t) \]  

and

\[ r_2(t) = s_2(t) + n_2(t) = s(t/a - t_0) * p(t) + n_2(t) \]

where \( s(t) \) is the one-dimensional scattering distribution of the elastic target, \( p(t) \) is the impulse response of the ultrasonic system, \( n_1(t) \) and \( n_2(t) \) are uncorrelated renditions of random noise and \( * \) denotes convolution. The constant

\[ a = 1 - \varepsilon \]

is close to unity, because the applied strain \( \varepsilon \) is generally small for conventional elastography (\( \varepsilon \leq 0.01 \) [5]).

Pre- and postcompression echo signals are jointly non-stationary because the displacement between them is

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depth-dependent. Moreover, because of the compression of the tissue, the postcompression signal is not an exact delayed replica of the precompression signal, resulting in decorrelation that increases with increasing strain. Temporal stretching [10], [11], [13] of the postcompression signal by the appropriate factor has been shown to significantly improve its correlation with the precompression signal and compensate for the effect of compression fairly well at low strains [12]. However, the proper temporal stretching factor is dependent on the local strain, an unknown parameter we are trying to estimate. Moreover, in an elastically inhomogeneous tissue, the strains will vary and, thus, the stretching factor will have to be varied at different windows. This is why a global uniform stretching of the entire postcompression RF line is not ideal for imaging real tissue. Because temporal stretching by the factor that compensates for the strain maximizes the correlation, an iterative algorithm is indicated. In this algorithm, the local temporal stretching factor is adaptively varied until a maximum in the correlation is reached. When the maximum is reached, the local strain is computed directly from the temporal stretching factor that maximized the correlation.

The effect of temporal stretching is illustrated in Figs. 1, 2, and 3. In Fig. 1 we show the simulated pre- and postcompression signals for a 2% applied strain. Then we temporally stretched the postcompression signal by the same factor by which the tissue was compressed. The precompression signal and the stretched postcompression signal are much more similar than the pre- and the postcompression signals. But, they are not exact replicas of each other, due to the fact that the system transfer function embedded in the postcompression signal is also stretched [note (3)]. To determine their similarity, we have plotted the autocorrelation coefficient function for the precompression signal, \( \rho_{11}(\tau) \) and the cross-correlation coefficient functions for the pre- and postcompression signals, \( \rho_{12}(\tau) \) and for the precompression signal and the temporally stretched postcompression signal, \( \rho_{13}(\tau) \) in Fig. 2. Note that \( \rho_{11}(\tau) \) and \( \rho_{13}(\tau) \) are very similar. To inspect them more closely, these are plotted around their peaks in Fig. 3. The peak value of \( \rho_{11}(\tau) \) is 1. The peak value of \( \rho_{12}(\tau) \) is 0.9573 and that of \( \rho_{13}(\tau) \) is 0.9978, showing that temporal stretching has significantly improved the correlation. The fact that appropriate stretching maximizes the correlation is used in the adaptive stretching algorithm.

If we temporally stretch the postcompression echo in (1b) by a factor \( 1/\alpha \), then:

\[
r_3(t) = r_2(\alpha t) = s_3(t) + n_3(t) = a s(t) * p(\alpha t) + n_3(t), \tag{3}
\]

\( n_3(t) \) is a time-scaled version of \( n_2(t) \).

The correlation coefficient function \( \rho_{13}(\tau) \) can be expressed as:

\[
\rho_{13}(\tau) = \frac{\int_{-\infty}^{\infty} r_1(t)r_3(t + \tau) dt}{\left(\int_{-\infty}^{\infty} r_1^2(t) dt \int_{-\infty}^{\infty} r_3^2(t + \tau) dt\right)^{1/2}},
\]

or,

\[
\rho_{13}(\tau) = \frac{\int_{-\infty}^{\infty} [s(t)*p(t)][a s(\alpha(t + \tau) - t_0) * p(\alpha t)] dt}{\left(\int_{-\infty}^{\infty} [s(t)*p(t)]^2 dt \int_{-\infty}^{\infty} [a s(\alpha(t + \tau) - t_0) * p(\alpha t)]^2 dt\right)^{1/2}}.
\tag{4}
\]

We have observed that the peak of \( \rho_{13}(\tau) \) maximizes when \( \alpha = a \) [12]. The Schwartz’s inequality for continuous
real signals \( g_1(t) \) and \( g_2(t) \) is expressed as follows:

\[
\text{if } \int_{-\infty}^{\infty} |g_1(t)|^2 dt < \infty \text{ and } \int_{-\infty}^{\infty} |g_2(t)|^2 dt < \infty,
\]

then

\[
\left| \int_{-\infty}^{\infty} g_1(t)g_2(t) dt \right|^2 \leq \int_{-\infty}^{\infty} |g_1(t)|^2 dt \int_{-\infty}^{\infty} |g_2(t)|^2 dt.
\]

For real signals, the equality is satisfied when \( g_1(t) = k g_2(t) \), \( k \) being a constant.

Thus,

\[
\left| \int_{-\infty}^{\infty} g_1(t)g_2(t) dt \right|^2 \leq \int_{-\infty}^{\infty} |g_1(t)|^2 dt \int_{-\infty}^{\infty} |g_2(t)|^2 dt
\]

or,

\[
\left| \int_{-\infty}^{\infty} g_1(t)g_2(t) dt \right| \leq \sqrt{\int_{-\infty}^{\infty} |g_1(t)|^2 dt \int_{-\infty}^{\infty} |g_2(t)|^2 dt}
\]  \[ (5) \]

If we choose \( g_1(t) = s(t) * p(t) \) and \( g_2(t) = \alpha s \left( \frac{t}{\alpha} \right) * p(\alpha t) \), then

\[
\rho_{13\text{max}} = \frac{\int_{-\infty}^{\infty} \left[ s(t) * p(t) \right] \left[ \alpha s \left( \frac{t}{\alpha} \right) * p(\alpha t) \right] dt}{\sqrt{\int_{-\infty}^{\infty} [s(t) * p(t)]^2 dt \int_{-\infty}^{\infty} \left[ \alpha s \left( \frac{t}{\alpha} \right) * p(\alpha t) \right]^2 dt}} \leq 1.
\]  \[ (6) \]

We have removed \( t_0 \), present in (4), in (6) because it is a delay term and will only affect the location of the correlation peak (something we are not interested in), and not its magnitude (the parameter of interest).

We have observed that temporal stretching of the postcompression signal maximizes the correlation between the pre- and postcompression signals [12]. The correlation recovery occurs due to the effective realignment of the scatterers, and the stretching of the system impulse response has little effect at low strain. Thus, we ignore the stretching of the system impulse response and write \( p(\alpha t) = p(t) \) for \( \alpha \approx 1 \). Now we can write (6) as:

\[
\rho_{13\text{max}} = \frac{\int_{-\infty}^{\infty} \left[ s(t) * p(t) \right] [s \left( \frac{t}{\alpha} \right) * p(t)] dt}{\sqrt{\int_{-\infty}^{\infty} [s(t) * p(t)]^2 dt \int_{-\infty}^{\infty} \left[ s \left( \frac{t}{\alpha} \right) * p(t) \right]^2 dt}} \leq 1.
\]  \[ (7) \]

\( \rho_{13\text{max}} \) maximizes when \( g_1(t) = k g_2(t) \), which clearly happens only when \( \alpha = \alpha \). Thus, it is possible to estimate the strain by locating the cross-correlation coefficient maximum between the pre- and postcompression echo signals when the appropriate stretch factor is chosen; the stretch factor itself then becomes the estimator of strain. This suggests an adaptive algorithm, which we illustrate in Fig. 4. We have performed a 1-D simulation of 2% compression. Then we attempted to stretch the postcompression echo signals using various stretch factors corresponding to strain values from 0 to 4%. We computed the correlation coefficient between the pre- and stretched postcompression signals. A 2 mm window was used. The correlation coefficient maximized at a stretch factor corresponding to the true 2% strain, and, thus, the stretch factor that maximizes the correlation between the pre- and postcompression signal can be used for estimating strain.

The algorithm is shown using a flow-chart in Fig. 5. The flow-chart demonstrates strain estimation for this method only at one data window location. To obtain the elastogram, this must be repeated at all locations. In this method, as already discussed, we iteratively stretch the postcompression signal by various stretch factors until we reach a maximum in the correlation coefficient function peak.

**B. Search Algorithms**

In the algorithm described in Fig. 5, the shaded box (to choose the next value of \( \alpha \)) is of paramount importance. For computing the strain, we need to determine the stretching factor that maximizes the correlation between the pre- and postcompression signals. This can be done using an exhaustive search. However, the exhaustive search is computationally intensive. We have used the binary search method. The method is illustrated in the flow-chart in Fig. 6. In the binary search method, an initial search interval needs to be chosen. Of two current stretch factors, the one producing the larger correlation is retained, and the search interval is halved, until a stopping criterion is reached. Various other search algorithms may be used in its place, such as a hierarchical search [14]. It also is possible to invoke binary search after initially investigating a few equally spaced stretch factors. That will reduce the possibility of locking onto a false maximum.
III. SIMULATION AND PHANTOM EXPERIMENT

An FEM simulation was performed using the ALGORD software to investigate the performance of the new estimator. We simulated a 2-D phantom containing three hard inclusions in a uniform background. In the ideal elastogram in Fig. 7(a), the inclusion at bottom left is 10 dB harder than the background (20 kPa). The inclusion on the right and at top left are 20 and 40 dB harder, respectively. The strain variation in the other regions is due to stress-concentration [15], [16] and other mechanical artifacts. For the simulated round-trip transfer function, the center frequency was 5 MHz, and the fractional bandwidth was 50%. The data were sampled at 48 MHz. White noise was added to the A-lines to obtain an SNR of 30 dB. The simulation was repeated after confining the phantom in the lateral direction [17]. We also performed another FEM simulation of a 2-D homogeneous phantom to investigate and isolate the effect of lateral confinement. For all simulations, a plain strain model was assumed.

We then performed a phantom experiment to investigate the performance of the new estimator. A gel-based tissue-mimicking phantom was used. The phantom contained...

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tained a 2 cm single hard inclusion, with a modulus contrast of approximately four. The phantom was not laterally confined. The data were collected using a Diasomics Spectra scanner with a 7.5 MHz linear transducer. The data were sampled at 48 MHz.

Using MATLAB, we simulated linear strain profiles to test the adaptive stretching method at varying strains. Then, we simulated chirp strain profiles to investigate the ability of the adaptive stretching technique to track strain when the rate of change of strain varies. We used 64 lines of 3072 uniformly spaced, Gaussian distributed random amplitude scatterers within a transducer beam, with 10 scatterers per wavelength. The round-trip transfer function had a center frequency of 5 MHz and a noise equivalent bandwidth of 60%. The signals were sampled at 50 MHz. The RF A-lines were computed by convolving the scatterer profile with the impulse response of the system. Tissue compression was simulated by appropriately time-shifting the scatterers, implemented using a frequency domain algorithm. White noise was added to the RF signals to obtain an SNR of 40 dB.

Temporal stretching was performed using interpolation algorithms. It is necessary to accurately estimate the peak value of the correlation coefficient function. Thus, to avoid using interpolation to locate the peaks and introduce further error, the A-lines needed to be sampled at a high sampling rate. For all the cases, the RF lines were resampled at 500 MHz using a bandlimited interpolation routine, prior to adaptive stretching. Prior to temporal stretching and the correlation coefficient function evaluation, the signals were decimated to reduce the computational complexity.

IV. Results

The results for the FEM simulation described in the previous section are shown in Figs. 7, 8, 9, 10, 11, and 12. The elastograms obtained using various methods are shown in Fig. 7 for a 1% strain applied to the inhomogeneous phantom. The correlation window size was 2 mm, and we used a window overlap of 75%. No additional filtering was performed on these elastograms to reduce the noise. The ideal (FEM) elastogram is shown in Fig. 7(a). The elastogram in Fig. 7(c) using displacement gradient method shows some noise, especially in the high strain areas. The elastogram in Fig. 7(d) produced using the displacement gradient method in conjunction with a global uniform stretching (by the average strain) performs better. However, it has some very noticeable artifacts. Clearly, the elastogram in Fig. 7(b) produced using the adaptive stretching is the closest to the ideal, and also has the lowest visual noise of the three. When the applied strain was increased to 2%, the gradient method produced a very noisy elastogram [Fig. 8(c)]. When the gradient method was used in conjunction with global stretching [Fig. 8(d)], the performance was significantly improved, but the elastogram still had artifacts similar to Fig. 7(d). Adaptive stretching [Fig. 8(b)] produces the elastogram that is closest to the ideal, and which has the lowest visual noise.

In Fig. 9, we compared the performance of adaptive stretching with that of the gradient method (with uniform stretching) at various strain levels for the above FEM simulation. Fig. 9(a) contains elastograms using the gradient method (with uniform stretching) at various strains. An ideal elastogram at 1% applied strain is also shown. The elastograms appear satisfactory but are dominated by the above mentioned artifacts at low applied compressions and by large noise at high applied compressions. Fig. 9(b) contains elastograms processed from the identical data set using adaptive stretching along with an ideal elastogram at 1% applied strain. These elastograms are significantly less noisy, free from artifacts, and closer to the ideal. At higher applied compressions, some noise begins to appear. If we carefully examine these elastograms, we observe that there is an increasing trend in the noise away from the lateral center of the image. This is due to the fact that, when the tissue is compressed, scatterers that are not on the beam axis of the transducer move in the axial as well as the lateral direction, introducing additional decorrelations. The larger the applied compression, the larger the lateral motion near the edges. The elastograms at larger compressions, therefore, appear noisier around the vertical edges of the phantom. To investigate this issue, we performed a simulation where the tissue was laterally constrained [17], thereby minimizing the movement of the scatterers in the lateral direction. These elastograms are shown in Fig. 9(c). We observe an improvement in the noise characteristics in all the elastograms, but the improvement is more apparent in the elastograms at larger applied compressions and is especially noticeable at the largest applied compression. All
Fig. 9. FEM simulation. (a) Gradient with uniform stretching, (b) adaptive stretching and (c) adaptive stretching (phantom laterally confined).
the elastograms were processed with 2 mm window size and 75% window overlap. The elastograms in Figs. 9(b) and (c) have slightly different appearances and contrast because lateral confinement affects the boundary conditions, which would generally cause changes in the internal strains in the target. Thus, lateral confinement may be useful in reducing the degradation due to lateral decorrelations. A lateral tracking method proposed by Chaturvedi et al. [18] to compensate for the lateral movement of the scatterers also may be useful in compensating for the lateral decorrelation. Konofagou and Ophir [24] have proposed a method that can estimate the lateral displacement with high precision and produce excellent corrected axial and lateral elastograms.

Because correlation may be lost due to various factors that include lateral movement of the scatterers, we wanted to isolate lateral movement. This was not possible in the inhomogeneous phantom [Fig. 9(c)] because the decorrelation is dependent not only on the lateral movement of the scatterers but also on the strain nonuniformities due to the inhomogeneities. Therefore, we performed another FEM simulation of an elastically homogeneous phantom. In Fig. 10, we show the resulting elastograms using adaptive stretching for unconfined and laterally confined tissues for applied strains of 2 and 4%. We also plot the mean correlation coefficient between the pre- and the adaptively stretched postcompression A-lines (averaged over depth) versus the lateral position for both confined and unconfined cases. For 2% applied strain, the correlation coefficient drops from a maximum of 0.993 at the lateral center to about 0.975 at the vertical edges. For the 4% applied strain, the maximum achievable correlation coefficient at the lateral center is still 0.985. However, the higher compression reduced the correlation coefficient at the vertical edges to around 0.91. The application of lateral confinement made the correlation independent of lateral position. Similarly, the elastograms for the unconfined cases have larger visible noise around the vertical edges, and this trend is removed in the laterally confined phantoms.

In Fig. 11, we compare the performance of all the methods by evaluating how similar they are to the ideal elastogram. We have computed the correlation coefficient between the ideal and the estimated elastograms in conjunction with necessary image registration. The gradient method without stretching degrades very fast as the compression is increased beyond 1%. The gradient method with uniform stretching performs much better at strains larger than 1%; the correlation with the ideal elastogram maximizes at ~3% applied strain and then starts decreasing. Adaptive stretching, however, performs the best at all applied compressions. However, we must point out that the correlation coefficient between the ideal and the estimated elastograms sometimes may tend to underestimate the image degradation in some areas of the elastograms. This is because the correlation coefficient is evaluated for the entire elastogram and there may be errors only at some specific locations (such as the noisy low strain regions at larger applied compression for gradient method with uniform stretching), which may be reduced by averaging the error over the entire image.
In Fig. 12, we extend the investigation to the effect of lateral confinement on adaptive stretching. In Fig. 12(a), we evaluate the correlation coefficient between the estimated elastogram and the ideal elastogram (similar to Fig. 11). As expected, we obtain better correlation for the confined phantom. This correlation coefficient again tends to underestimate the degradation in the unconfined phantom. Thus, to get a further understanding on this issue, we also plotted in Fig. 12(b) the mean value of the correlation coefficient between the pre- and the postcompression A-lines (after adaptive stretching) around the vertical edges of the phantom for both the unconfined and confined cases. We observe that, without confinement, the maximum achievable correlation decreases rapidly with increasing strain. When lateral confinement is applied, this rate slows considerably.

To investigate the useful range of strains for adaptive stretching, we simulated 64 A-lines using a 1-D model with identical linear strain profiles (the 1-D model was used to investigate only the effect of strain, isolating it from the other phenomena). The maximum strain simulated was 25%. Center frequency was 5 MHz, and bandwidth was 60%. A 2 mm data window was used with 50% overlap.

We have plotted the mean and standard deviation of the estimated strain profiles for all the A-lines (Fig. 13). We also plotted the true simulated strain profile. As expected, adaptive stretching performs very well at low strains. The mean estimated strain is almost equal to the true strain with low standard deviations for strains lower than ~7%. For larger strains, the standard deviation begins increasing, and some random bias is observed in the mean of the estimated strain. At strains larger than ~12%, there is a systematic negative bias error. We believe that this is due to the fact that, at these strains, temporal stretching can no longer adequately reverse the decorrelation introduced by the tissue compression. The magnitude of the standard deviation at high strains may be partially limited by the limited search range of the algorithm.

To test the limits of the adaptive stretching estimator in the presence of rapidly varying strains, we have simulated strain profiles that look like FM chirps. We simulated 64 A-lines, each with identical strain profile of more than 30 cycles. The minimum and maximum strains were 0 and 4%, respectively. The rate of change of strain increases linearly with depth. Farthest from the transducer, the spatial period of the strain sinusoid is less than 1 mm. The center frequency was 5 MHz and the bandwidth was 60%. A 1 mm data window was used with 88% window overlap to adequately sample the strain variation at all depths. Figs. 14 and 15 show the performance of adaptive stretching compared to that of the displacement gradient method for the chirp strain profiles. In Fig. 14, the adaptive stretching method follows the true strain profile quite well only in the first half cycle. When the rate of change of strain increases, the technique begins to show difficulty in following the strain profile, especially at the maxima and the minima. Fig. 15 shows the estimated strain profiles for both gradient methods (with and without stretching). The gradient method without stretching is practically useless in tracking the strain variation. If stretching is applied, the gradient method is capable of reproducing the strain profile at least when the rate of change is small; however, the contrast is drastically lower than that in the true strain profile.

We also have tested the utility of adaptive stretching using experimental data. We computed elastograms using the adaptive stretching method applied to data from
Fig. 13. 1-D simulation showing the performance degradation of adaptive stretching as strain increases.

Fig. 14. 1-D simulation for chirp strain profile. Adaptive stretching.

Fig. 15. 1-D simulation for chirp strain profile. Gradient methods.

Fig. 16. 1-D simulation for chirp strain profile. Gradient methods.

V. DISCUSSION AND CONCLUSIONS

We have proposed a novel nongradient strain estimator in this article. We have demonstrated that it performs significantly better than the conventional displacement gradient estimators, and have discussed the characteristics and limitations of the new estimator. We have previously demonstrated that temporal stretching of postcompression signals can significantly reduce signal decorrelation [12]. However, the proper stretch factor depends on the local strain, which is the unknown quantity we are trying to estimate. To overcome this dilemma, an adaptive iterative algorithm is proposed that searches for the stretch factor that maximizes the correlation between the pre- and postcompression echo signals. This stretch factor itself then becomes the estimator of strain. For homogeneous tissues, a displacement gradient method can be applied to uniformly stretched data. In inhomogeneous targets, adaptive stretching is desirable because different segments of the echo may need different amounts of stretching. Because we maximize the axial correlation at each data window between the pre- and postcompression A-lines, this estimator is an “optimal” estimator of strain. Gradient operation amplifies noise in the displacement estimates. Because adaptive stretching does not contain any inter-window operation, it does not suffer from this type of degradation. Overall, adaptive stretching may help improve the elastographic performance by a large factor. In addition to the necessity to obtain low noise and accurate elastogram for precise diagnosis, if we attempt to compute true elasticity map from the strain map, the accuracy of the former will heavily depend on that of the latter.

If adaptive stretching cannot be performed for any reason, a global uniform stretching of the postcompression A-line in conjunction with the displacement gradient method is advisable, especially if the applied strain is larger than 1%. However, the global stretching may itself be the cause of some degradation. In our studies, it introduced some artifacts in the elastograms of the inhomogeneous FEM phantom at low applied compressions, which we have verified to be due to reduced correlation values. At higher applied compressions of the same phantom, the elastograms
Fig. 16. Inhomogeneous phantom experiment; 0.5% applied strain. Window size = 2 mm. Window overlap = 50%. Median filtering $3 \times 3$. Elastograms: (a) gradient, (b) gradient with stretching, and (c) adaptive stretching. The "cross" shape in the elastograms is due to mechanical stress-concentration effects [15], [16].

Fig. 17. Inhomogeneous phantom experiment; 2% applied strain. Window size = 3 mm. Window overlap = 50%. No median filtering. Elastograms: (a) gradient, (b) gradient with stretching, and (c) adaptive stretching.

have significant noise in the low strain areas. This can be attributed to the fact that uniform stretching may itself introduce significant decorrelations in the low strain regions by over-stretching the postcompression signal. Note that, as expected, the noise in these elastograms begins in the lowest strain regions, and gradually "leaks" into the higher strain regions as the applied compression is increased. Another point of note is that identically processed elastograms of the phantom data do not exhibit similar artifacts. We also do not observe the drastic increase in the noise in these elastograms in the areas of low strain. This can be attributed to the fact that the elasticity contrast in the experimental phantom was only about 10 dB, whereas it was more than 40 dB in the FEM simulation. However, in human breast tissue containing tumors, the strain dynamic range could be larger than 30 dB [19] and uniform stretching may be susceptible to these effects. Interestingly, the lowest contrast (10 dB) inclusion in the FEM simulation was also relatively free from these effects. It is of interest to note that, despite the large strain dynamic range in the phantom, it was possible to distinguish the three inclusions in the elastograms produced by adaptive stretching. In conventional gradient-based elastography, the dynamic range is much smaller. Konofagou et al. [20] developed a method to expand the dynamic range in conventional elastography by increasing the dynamic range of the applied strain. Such expansion may become unnecessary when adaptive stretching is used [25].

In displacement estimation, two types of errors occur. The first type of error is commonly called the false peak [21] or the peak hopping error. False peaks occur when noise and signal decorrelation increases the height of a secondary correlation peak above that of the true peak. The second type of error is called the jitter error, which occurs due to the slight displacement of the true correlation peak due to noise, signal decorrelation, and sampling. At high SNR and low strain, this type of error is the most common [22]. However, at large strains and/or low SNR, false peak errors can become more common and can degrade both the gradient and adaptive stretching methods (a false peak at a wrong stretch factor may be larger than the true peak at correct stretch factor). However, because the gradient method uses two consecutive windows to estimate strain, one false peak error will introduce large errors to two consecutive strain estimates. By contrast, with adaptive stretching, one false peak error produces only one erroneous strain because only one window is used. Moreover, the peak value (and not location) of the correlation coefficient is used to estimate the stretch factor. Thus, a false peak means that the next pre- and postcompression echo segments are not aligned properly. As a result, the location of the peak for these segments will not be at $t = 0$, but can be accurately estimated unless there is another unlikely false peak error.

Choosing the proper correlation window size is of utmost importance. Because elastographic resolution is related to the correlation window size [11], choosing smaller windows will result in better resolution. However, our experience showed that window sizes significantly less than 2 mm produce noisy images for the displacement gradient
and adaptive stretching methods. If the strain is constant or slowly varying, then choosing a large window is expected to improve the SNR of the strain estimates. However, because tissue is inhomogeneous, a very large window means that there will be significant variations in the strain within the window, and the performance of adaptive stretching will suffer as a result because it implicitly assumes constant strain within the window. There is an optimum between the case when the window is too small, resulting in noisy elastograms, and the case when the window is too large, resulting in significant strain variations within the window. The optimal window size will, of course, depend on various parameters. It is advisable to use the smallest window size that will produce strain estimates with low noise. We have determined that a window size of about 2 mm produces strain estimates with acceptable SNR in most cases. However, we had to use a slightly larger window for the phantom data at larger strains. One-dimensional simulation of chirp strain profiles (Fig. 14) have shown that, at very high rate of change of strain, the adaptive stretching algorithm cannot follow the strain profile very well and cause a decrease in estimated chirp amplitude. This is due to the considerable variation of strain within a correlation window at larger depths and the estimate by adaptive stretching is close to the mean strain within the correlation window. Thus, a modulation transfer function (MTF) approach [23] may be used to define elastographic resolution. The resolution may be defined from the spatial period of strain sinusoid at which the estimated strain decreases by a certain factor from the maximum.

We performed an extensive study of the new estimator using the 2-D FEM simulations. A limitation of the 2-D simulation is that it does not include the movement of the scatterers in the elevational direction. However, the ultrasonic beam in currently available 2-D arrays is much wider in the elevational direction compared to the lateral direction. Thus, the scatterer movement in the elevational direction does not cause significant loss of coherence in the echoes, and this limitation of the 2-D simulation is currently not a cause for great concern. The results from the experimental phantom data naturally included the 3-D geometry.

The performance of adaptive stretching degrades as strain increases as shown in Fig. 13. This is due to the fact that temporal stretching of the post-compression echo is not an exact inverse of the tissue compression [see (3)], especially at large strains. However, we have observed adaptive stretching to degrade more slowly than the gradient-based methods at higher strains. At a very small applied compression, the SNR will be low because the signal itself (strain) is low. Thus, it is desirable to use the highest applied compression that does not begin degrading the strain estimates to maximize the SNR in the elastograms. To obtain elastograms with the best SNR, it is advisable to limit the applied compression to within that value. However, it may not always be possible to know that compression level in advance. It might appear from the 1-D simulation that adaptive stretching may produce usable strain estimates up to strain levels of 10 to 15%. However, this simulation does not include any effects expected in the experiments, including lateral or elevational movement of the scatterers. Also, it does not include any nonlinear behavior in the tissue that is expected at high strains. When all these effects are taken into account in a real experiment, we expect the adaptive stretching estimator to begin failing at lower strains (possibly in the 5 to 10% range).

Another current limitation of adaptive stretching is its computational complexity. Because it is an iterative procedure, the time required to produce elastograms is about one order of magnitude greater than that required for the gradient methods. However, we have thus far made only minimal attempts to reduce the computational complexity of this method.

Adaptive stretching, at least in the present implementation, does not reduce the decorrelation due to lateral and elevational movements of scatterers. Larger compression may be desirable up to a point to increase the SNR. Because increasing the strain also increases the lateral motion away from the lateral center, the lateral decorrelation may introduce errors in computing the best stretching factors and, thus, in the strain estimation. The FEM simulations demonstrated that the maximum achievable correlation between the pre- and postcompression A-lines decreases away from the lateral center and that lateral motion causes adaptive stretching to produce noisier elastograms at the vertical edges, but the gradient methods have also been shown to be susceptible [17]. The methods for correcting lateral displacement may substantially improve the elastographic SNR.

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"A. ALAM et al.: AN ADAPTIVE STRAIN ESTIMATOR 471"


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