ELASTOGRAPHIC DYNAMIC RANGE EXPANSION USING VARIABLE APPLIED STRAINS

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In elastography, we want to image the entire range of stiffnesses of the elastic components found in
inhomogeneous tissues. In order to achieve this, the elastographic dynamic range should exceed the en-
tire stiffness dynamic range in the target. Various sources of noise limit the dynamic range of elastogra-
phy. The recently-defined strain filter concept offers an analytical and graphical way of observing these
limitations. In this paper, we describe a method that achieves the expansion of the elastographic dy-
namic range. It involves the application of variable strains in combination with selective storage of
strain data that have optimal elastographic signal-to-noise ratios. This expands the current dynamic
range of elastography by orders of magnitude when compared to single compression elastography. The
process is explained theoretically using the strain filter framework, and 1D as well as 2D tissue simula-
tions are used to corroborate the theory.

KEY WORDS: Correlation; dynamic range; elastogram; elastography; imaging; multicompression; stiff-
ness; strain; strain filter; ultrasound. © 1997 Dynamedia, Inc.

I. INTRODUCTION

Most pathological changes are related to changes in tissue stiffness. Elastography is a
technique that uses ultrasonic signals for the estimation of tissue stiffness. Figure 1 schematic-
ally shows the main steps followed in elastography. When compressed, the tissue is
strained (tissue strain). Elastography consists of transmitting ultrasonic pulses into the tissue
before and after compression. It then uses signal processing methods to generate an image
(elastogram) showing the estimated (axial) strains in the given tissue.

The axial strain values are calculated by estimation of the axial displacement gradients of
tissue components due to the compression (axial being defined along the direction of the ul-
trasonic beam). The final image is produced by assigning dark and light gray levels to low
and high strains, respectively. High and low strains are usually associated with soft and hard
tissue regions.

One of the challenges in the development of this modality consists of providing an image
with the largest attainable range of strains corresponding to the stiffnesses of various struc-
tures. In most applications, we deal with a heterogeneous volume of tissue, such as the
breast. Such a tissue body may contain fat, fibrous, glandular and tumors tissues. The
range of stiffnesses spanned by these structures is typically several orders of magnitude. For
example, in the breast, the fat is considered soft (with an average stiffness modulus of 14
kPa), while a tumor consists mainly of hard tissue (e.g., a scirrhous carcinoma with an aver-
age stiffness modulus of 660 kPa). This gives an estimate of the stiffness dynamic range in
the breast of around 35 dB. Sarvazyan has reported that the stiffness dynamic range in the
breast can be as high as 60 dB. In addition, another important aspect of expanding the dy-
namic range is that it offers a greater ability to distinguish between tissue components of
similar material content but different stiffnesses. This is, for example, the case of a fibroade-

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nomma and a scirrhous carcinoma, where the former is a benign and the latter a malignant tumor with a difference in stiffness of 10 dB or less. In order to diagnose them properly, the elastographic dynamic range should be high enough so as to be able to assess their strains (and therefore stiffnesses) correctly.

In such a heterogeneous tissue, small strains may develop in harder tissue regions, which may be obscured by random noise effects (e.g., electronic and quantization noise) when small strains are applied. At large compressions, however, signal decorrelation noise may make the strain estimates in the softer tissue very noisy. Therefore, when using a single compression, the strain image of the tissue will have a limited dynamic range, as depicted by the width of the strain filter (to be discussed later).

In this paper, we describe a method that takes these observations into account in order to expand this limited dynamic range. It also makes use of the fact that the applied strain can be an equally important input parameter in the elastographic process (Fig. 1). In other words, this method relies on increasing the dynamic range of the applied strain in order to expand the dynamic range of the estimated strain; it no longer makes use of strain data corresponding to a single compression, but rather selects the optimal strain data from a collection of elastograms corresponding to variable applied compressions. The tool that is used to pick the optimal strain corresponding to each compression level is the strain filter, which estimates the elastographic signal-to-noise ratio (SNR) for each value of estimated strain. The strain filter is described below and in appendix A.

II. THEORY

In this section, the strain filter concept is explained. We also describe the principle behind the dynamic range expansion method.

Strain filter

Strain estimation in elastography involves the use of pulse-echo ultrasound in combination with time-delay estimation (TDE). Both introduce noise artifacts into the elastographic image process. The ultrasonic signals that are acquired are corrupted by speckle, electronic and quantization noise. In addition, the compression of unresolvable acoustic scatterers in the tissue results in distorted postcompression signals. In other words, the tissue speckle pattern before and after compression is different, leading to speckle decorrelation. In elastography, crosscorrelation is performed under the assumption that the postcompression signal is a
delayed version of the precompressed signal within a small region of interest. However, the normalized crosscorrelation coefficient function used for TDE never achieves a unity peak value, as it would in the case of a pure time delay. The resulting decorrelation increases with increasing tissue strain. Elastography is thereby limited on the high end to strains smaller than 1-2%. This is because, as strain rises, decorrelation noise increases and, therefore, many peak-hopping errors occur. This happens when the variance of the strain estimation goes into the Barankin region, as depicted by the strain filter and reference 7. However, if we use baseband waveforms, this limitation is significantly relaxed.6

On the low end, for very small tissue strains, elastographic performance is bounded by the classical lower bound on the TDE variance, the Cramér-Rao Lower Bound (CRLB) due to random noise sources. These two bounds define the performance limits of elastography; it is expected that its performance would be optimal somewhere between these two limits.6

Based on these observations, the Strain Filter (SF) concept, recently developed by Varghese and Ophir, demonstrates mathematically and graphically the aforementioned limits. Its name borrows from the fact that it usually presents a bandpass filter behavior in the strain domain, i.e., the elastographic process selects a restricted range of actual tissue strain to be included in the estimated strain data (Fig.1). The rest of the actual tissue strain data is not measurable and, therefore, appears very noisy on the elastogram.

The theoretical SF (Fig. 2) is generated by plotting the upper bound of the SNR vs. the tissue strain for a given level of desired elastographic axial resolution (see appendix A). The reader should note from figure. 2 that the maximum SNR, is reached inside the CRLB region of the strain filter. When the lower bound coincides with the Barankin Bound (see appendix A), the performance of the strain filter drops sharply, with a further drop in performance observed when the variance reaches the constant level.6

FIG. 2 A typical theoretical strain filter, the DR, is shown here as its -6 dB width. Sensitivity is denoted here by \( \varepsilon \text{, max} \). Note that the maximum of the strain filter occurs in the CRLB region of the strain filter.
The -6 dB width of this bandpass characteristic may be defined as the *elastographic dynamic range* (DR). It may also be defined as the logarithmic ratio of maximum-to-minimum estimated strain values $e_{\text{emax}}$ and $e_{\text{emin}}$ (both taken at the -6 dB SNR, value, Fig. 2), respectively, i.e.,

$$DR_e = 20 \log_{10} \frac{e_{\text{emax}}}{e_{\text{emin}}}$$

(1)

where $DR_e$ represents the range of strains in target regions over which high elastographic strain estimates may be made. The low-strain behavior of the SF (or the value of $e_{\text{emin}}$) is determined by the postintegration SNR (see appendix A), whereas the high-strain behavior (or the value of $e_{\text{emax}}$) is determined by the degree of decorrelation of a pair of congruent signals.

According to the defining equation (see appendix A, Eq. A2), the strain filter mainly depends on the signal processing specifications (e.g., window size and overlap factor) and the technical parameters of the ultrasound system, such as bandwidth, center frequency and sonographic SNR. Therefore, one possible way of increasing $DR_e$ would be an appropriate modification of the ultrasonic system parameters. However, previous work has shown that the subsequent improvement in the $DR_e$ is generally small. To demonstrate this effect, a typical example of varying the center frequency is illustrated in figure 3. From figure 3, if we compare the graphs corresponding to center frequencies of 5 MHz and 7.5 MHz, we find an increase in the SNR by a factor of two (the maximum SNR is 5.8 and 11.6 for 5 MHz and 7.5 MHz, respectively). Although the SNR increases with the center frequency by a factor of two, the resulting increase in the $DR_e$ is rather unremarkable given the expansion by orders of magnitude required by the tissue, as explained in the introduction. Similar results are obtained with an increase in the bandwidth or the window size. No significant change is also noted when multicompression or A-line averaging is used. In the following section, we describe a technique that achieves a significant expansion of the dynamic range, using a selective method of estimating strains from variable applied strain elastograms, while maintaining the same technical parameters.

**Expansion technique**

The dynamic range of the tissue stiffness (DR) is defined as the logarithmic ratio of the maximum-to-minimum elastic (Young's) modulus of all the structures in tissue:

$$DR_r = 20 \log_{10} \frac{E_{\text{t max}}}{E_{\text{t min}}} \approx 20 \log_{10} \frac{e_{\text{t max}}}{e_{\text{t min}}}$$

(2)

where $E_{\text{t max}}$ and $E_{\text{t min}}$ are the highest and lowest tissue elastic moduli, while $e_{\text{t max}}$ and $e_{\text{t min}}$ denote the maximum and minimum tissue strains, respectively. The relationship on the right side of Eq. 2 assumes a proportionality between the strain and the inverse of the modulus (assuming constant and nonzero stress throughout the target). Ideally, the elastographic dynamic range DR should equal the stiffness modulus dynamic range DR. However, due to the limited bandwidth of the strain filter, we usually have

$$DR_e < DR_r$$

(3)

$$\frac{e_{\text{emax}}}{e_{\text{emin}}} < \frac{E_{\text{t max}}}{E_{\text{t min}}}$$

(4)
In order to overcome this limitation, we use variable applied strains. We define the dynamic range of the applied strain $DR_a$ by

$$DR_a = 20 \log_{10} \frac{\varepsilon_{a\text{ max}}}{\varepsilon_{a\text{ min}}}$$

where $\varepsilon_{a\text{ max}}$ and $\varepsilon_{a\text{ min}}$ are the maximum and minimum applied strains, respectively. $DR_a$ represents the range of applied strains, for which elastograms have been generated.

Since in elastography we are generally dealing with applied strains of less than 2%, we can assume that both the actual and the estimated tissue strains depend linearly on the amount of applied strain. According to the general equation $\sigma = E\varepsilon$, where $\sigma$ is the stress, $E$ is the Young’s modulus and $\varepsilon$ is the strain, the strain is also inversely proportional to the Young’s modulus or stiffness of the tissue assuming the stress stays constant, which in cases of small applied strains is a valid assumption to make. So, for small applied strains, the strain estimated $\varepsilon$ is directly proportional to the ratio $\varepsilon a / E$ and for a homogeneous tissue (fixed $E$), the estimated strain mainly depends on the applied strain.

We therefore hypothesize that by appropriately choosing the applied strain dynamic range $DR_a > 0$ dB, it would be possible to turn Eq. (3) from an inequality to an equality, viz.,

$$DR_e + DR_a = DR_f$$

(6)
Equation (6) implies that the entire tissue dynamic range can be depicted in the elastogram by using a sufficiently large $\text{DR}_a$. It also demonstrates the general principle behind the expansion of the dynamic range.

The expansion method consists of storing data corresponding to a finite dynamic range of applied strains ($\text{DR}_a > 0$ dB). We then select the optimal strain data, i.e., the data with maximum $\text{SNR}_c$ for each amount of applied strain. By proper scaling of the strain data (according to the corresponding applied strain), we obtain a composite elastogram with dynamic range such that

$$\text{DR}_c^C = \text{DR}_c + \text{DR}_a$$

(7)

Note that $\text{DR}_c$ itself becomes the $\text{DR}_c$ expansion parameter. Therefore, by proper selection of $\text{DR}_a$, the dynamic range of the composite strain filter could become ideal, viz.,

$$\text{DR}_c^C = \text{DR}_t$$

(8)

This method is fundamentally different from other techniques that use multiple compressions for noise reduction via averaging.\textsuperscript{11-12,14} Those techniques do not exploit the fact that $\text{DR}_c > 0$; they only average multiple (N) elastograms, corresponding to equal amounts of applied strain, in order to obtain a $\sqrt{N}$ improvement in the $\text{SNR}_c$. As a result, the $\text{DR}_c$ is limited to a small value. For a more detailed discussion on the effects of both multicompres'sion and A-line averaging on the $\text{DR}_c$, the reader should refer to appendix B.

The present technique applies variable strains ($\varepsilon_{\text{min}} \pm \varepsilon_{\text{max}}$) in order to achieve the dynamic range expansion, indicated by $\text{DR}_a > 0$. It also selects the optimal strain data from these variable applied strain elastograms, which can also be used for averaging to obtain further improvement of the $\text{SNR}_c$. The algorithm described below is based on this principle.

III. METHODS

Algorithm

Figure 4 shows graphically the method for extending $\text{DR}_c$. $N$ successive variable compressions are applied to the tissue. $N+1$ sonograms (including the precompression one) are acquired. The precompression sonogram is sonogram 0 and each elastogram is generated from the cumulative strain between the precompression and a postcompression sonogram. As a result, $N$ elastograms are generated corresponding to $N$ variable applied strains.

The method involves storing only the high strain data with high $\text{SNR}_c$ from the elastograms generated from low applied strain (thus, avoiding decorrelation) and the low strain data with high $\text{SNR}_c$ from the elastograms generated from high applied strain. These high $\text{SNR}_c$ strain data for each elastogram are found in the optimal region of the strain filter, as mentioned previously. As a result, the composite elastogram should ultimately contain each tissue strain value with its highest possible $\text{SNR}_c$ out of the multicompres'sion series. The resulting composite strain filter is wider and so is the $\text{DR}_c$ of the composite elastogram.

Since the optimal strains used for producing the composite elastogram correspond to variable applied strains, they must be normalized. The optimal strains are usually on the order of less than 0.5% (they have to be inside the optimal region of the strain filter). We can, thus, assume that, for these low values of strain, the estimated strain is linearly proportional to the applied strain. Therefore, in the composite elastogram, all the strains can be scaled according to the amount of applied strain to which they correspond. The normalization is per-
formed by scaling of the strain values obtained from each elastogram with respect to the corresponding amount of applied strain ($e_{aq}$) used to produce it. Since the composite elastogram is chosen to correspond to an applied strain of $e_{max}$, the scaling factor for the $q^{th}$ elastogram ($1 \leq q \leq N$) equals $e_{max}/e_{aq}$, where $e_{aq}$ is the applied strain used to produce it. This factor equals $N/q$ when the compression step is linear. Scaling corresponds to shifting the strain filter in the strain domain (dB) by $20 \log_{10} (e_{max}/e_{aq})$.

Figure 5 shows the steps involved in this DR expansion method in terms of the strain filter. The strain filter in this example is assumed fixed with $DR_e \approx 15$ dB (Fig. 5(a)) while the tissue under study has a $DR_e$ of 40 dB (Fig. 5(b)). The reader should note that the ideal expansion parameter $DR_e$ is 25 dB in this case (Eq. 6).

We consider the simple example where two compressions are applied with $DR_e = 20$ dB. The individual steps of this method are described below:

1. Initial compression ($e_{amin} = e_{aq}$): the higher strain (softer) areas produce strains that are found within the passband of the strain filter and they are stored (Fig. 5(c)). All other (noisier) strains are discarded due to their low SNR_e.

2. Second compression ($e_{max} = 10e_{aq}$): cumulatively higher strain is induced in the harder regions (Fig. 5(d)). These strains are now included in the strain filter range while the strains in the softer regions are now noisy and, therefore, discarded (Fig. 5(e)). They have already been stored, however, from the initial compression, with highest possible (optimal) SNR_e.

3. Scaling by $10/q$ of the stored data from the first ($q=1$) and the second ($q=10$) compression (Fig. 5(f)) in order to correctly assemble all the strain data corresponding to different compressions in the composite elastogram.

4. The composite elastogram (Fig. 5(g)): contains all the strain data correctly assembled from the two compressions (Figs. 5(e), (f)).
FIG. 5 Example in terms of the strain filter: (a) strain filter (of width $D_{R} \leq 15$ dB); (b) tissue strain of $D_{R} = 40$ dB (black=low, white=high); (c) stored strains due to initial compression; (d) second compression ($D_{R} = 20$ dB); (e) stored strains due to second compression; (f) scaling; and (g) resulting elastogram with $= 30$ dB. The grey scale has been used to graphically distinguish the hard (black) from the soft (white) tissue. See text for full explanation.

Figure 5(g) is interesting in two aspects. First, it shows that using data from two applied strains, the $D_{R}$ was expanded and the composite elastogram is a better approximation of the ideal case of figure 5(d) than the single applied strain case of figure 5(e). Second, it indicates that the $D_{R}$ has not been ideally expanded to equal the $D_{R}$ of 40 dB. There are two reasons for this: the $D_{R}$ (20 dB) used was smaller than the ideal (25 dB) and an expansion by only 15 dB was noted (equal to the width of the first compression SF). So, the theoretical amount of expansion, indicated by the $D_{R}$, can only be achieved if a sufficient number of compressions is used to cover that range, assuming that we start with the softest tissue strains within the passband of the strain filter (Fig. 5(c)).

Therefore, the performance of this expansion method depends on the specifications of the variable applied strain process. To further determine this, we borrow the term ‘ripple’ from filter design theory. We define ripple as the max-to-min difference of the $SNR_e$ within the passband of the composite strain filter. The smaller the ripple, the better the approximation of the ideal case of $D_{R}$. It is clear that in order to achieve the expansion of $D_{R}$ by the ideal amount (i.e., by $D_{R}$), the maximum amplitude of the ripple allowed is 6 dB. This is because of the definition of the $D_{R}$ as the -6 dB width of the strain filter. If the strain filters are over-
lapping at a level lower than -6 dB (Fig. 5(g)), then the dynamic range will be lacking those strain values that are found outside of the strain filter (Fig. 5(g), dotted line). To further approximate the ideal composite strain filter (rectangular, Fig. 5(d)), the ripple would have to be further reduced, with the ideal case being equal to 0 dB (no ripple). In the ideal case, the max-to-min difference of SNR, inside the passband would be zero i.e., the max-to-min ratio would be one and, in the dB domain, this would give 0 dB. This can be achieved by using a larger number of compressions to cover the DR, range, but this would also mean an increase in the amount of computation time in order to obtain the composite elastogram.

If we assume, for example, that the ripple amplitude is equal to 6 dB, the ideal DR, can be measured in the number of DR, ’s, indicating the minimum number of compressions to be used. So, in the example of figure 5, we have ideal DR, = 25 dB and DR, = 15 dB. Therefore, we would need at least 25/15 = 1.67 additional compressions to the single case (i.e., a total of 2.67 compressions at steps of 15 dB) to achieve the desired expansion by DR,. However, in the example of figure 5, we only used one additional compression, and the ripple was larger than the maximum allowed: the max-to-min SNR, difference was equal to the full amplitude of the strain filter (> 6 dB, Fig. 5(g)). Therefore, the resulting amount of expansion (15 dB) was less than DR, (25 dB).

To summarize, for a given number of compressions, there is a trade-off between the ripple and the desired expansion range. The ripple has to be sufficiently small so that the composite strain filter best approximates the ideal case (rectangular), i.e., all estimated strains have the same maximum SNR,. This requires high overlap between the shifted copies of the strain filter, i.e., using small compression steps in the variable applied strain process. On the other hand, large compression steps might be necessary to achieve maximum expansion of the DR,. Therefore, a safe way of using the variable strain approach would be to apply many compressions at a small step. This might, however, prove to be redundant in some tissue cases, as shown in the simulations to follow.

**SIMULATIONS**

**1D simulations**

The tissue strain profiles were simulated as one period of a spatial sinusoid, whose maximum and minimum correspond to the highest and lowest tissue strains, respectively. Therefore, the dynamic range of the simulated tissue could be modified by changing the appropriate parameters of the sinusoid. Since the elastographic dynamic range, as depicted by the strain filter, is on the order of 15 dB and the dynamic range of breast tissue can reach up to 60 dB, we chose to work with three different cases of simulated tissue dynamic range DR; 20, 40 and 60 dB (Fig. 6) so as to extensively test this method for the expansion of the dynamic range.

The simulated strain filters of figures 7 and 8 were all generated for the case of DR, = 40 dB. The simulated strain filters were generated by sorting all the actual tissue strain values in an ascending order and plotting them versus the corresponding SNR, values. The SNR, values are calculated as described in the appendix A. A 6-point moving average filter was also used to reduce the variation in the simulated strain filters. The 1-D profiles were smoothed out in order to arrange for a better graphical demonstration of the performance of the method. This kind of smoothing is not planned to be used in experiments with tissue, but instead we will definitely use the method of averaging described earlier.

The center frequency was fixed at 5 MHz with 60% fractional bandwidth and sonographic SNR equal to 40 dB. The scattering density in the media was set to 12.6 scatterers/wave-
length and the total scanned depth was equal to 100 mm. In all the simulations, a convolutional scattering model was used and crosscorrelation processing was performed using 3 mm windows with 0.5 mm shift between consecutive windows and a sampling frequency of 63 MHz.

The specifications for the dynamic range expansion method are the same for each case: N=20 compressions at a linear step $\varepsilon_s$ of 0.1% (i.e., $\text{DR}_s = 26$ dB). For a better representation of the results, we also provide the corresponding pseudo-2D profiles that were generated by stacking 100 independent renditions of the estimated 1D profiles. Both 1D and pseudo-2D profiles are smoothed out by averaging 100 uncorrelated renditions of simulated tissue and using a 6-point moving average filter. Finally, when averaging was used, random noise was
added to the signal with $\text{SNR}_e = 40$ dB. The noise was generated by a random generator and was added to both the precompression and the postcompression signals before cross-correlation. The power spectral density of the noise was normal. The process of averaging is explained more in detail in the results section.

### 2D simulations

In the case of the 2D simulation, we generated a finite-triangular-element phantom using the finite element analysis software ALGOR. We assumed slip boundary conditions and a linear, plane strain model. For more details about this model, the reader should refer to Kallel and Bertrand.\(^{19}\) The phantom was fixed at the bottom, free on the sides and compressed from the top by a compressor of size larger than the width of the target. This phantom had dimensions of 40x40 mm and contained three circular inclusions each of 8 mm diameter. The total stiffness dynamic range was 40 dB with the three inclusions at 10, 20 and 40 dB harder than the background. The background was homogeneous with a stiffness of 20 kPa. The ultrasonic parameters used were identical to those used for the 1D case. The size of the window used for signal processing was equal to 3 mm and the time overlap was of 50%. The dynamic range expansion method was applied using $N = 8$ compressions with $\varepsilon_a = 0.25\%$ incremental strain, i.e., a 2% total applied strain.

### IV. RESULTS

In figure 7, the single compression strain filter is shown shifted by different amounts according to the scaling factor used in each compression case. We note that the amount of ripple is well below 6 dB and the overlap of the shifted copies of the strain filter is large. In other words, the noisy strains for each compression (or strain filter) are discarded and are instead obtained from another (overlapping) SF where their $\text{SNR}_e$ are higher. Therefore, in the composite strain filter each strain estimate has its highest possible $\text{SNR}_e$, which results in an opti-
mal composite elastogram. The sensitivity (or, the minimum measurable estimated strain) of the composite strain filter has also been improved.

In order to further improve the SNR, in addition to expanding the DR, averaging between the elastograms corresponding to the same amount of compression may be used. Averaging is known to increase the amplitude of the strain filter, since it reduces the variance of the estimated strain (according to the number of uncorrelated elastograms used). Therefore, since the number of elastograms provided is different in each applied strain case, the averaged strain filter will have a different amplitude (effective SNR,) for each corresponding applied strain.

Figure 8 shows the effect of averaging. When comparing figures 7 and 8, it is obvious that when averaging is not used, the strain filter has the same amplitude for different applied strains. However, in the case with averaging, the SF amplitude will increase for smaller applied strains due to the larger number of uncorrelated elastograms available. Therefore, the composite strain filter obtained with the expansion method will have a different shape: without averaging, it maintains a nearly flat top (Fig. 7), while with added averaging, the amplitude increases on the high strain (softer tissue) side (Fig. 8).

In order to better understand this effect, we consider one more the example of figure 4. In this case, we have N multicompression elastograms. For averaging, we use elastograms corresponding to the same amount of applied strain. So, we would average over N-1 elastograms for the e_1 elastogram (i.e. SNR, improved by a factor of \( \sqrt{N-2} \), over N-2 elastograms for the 2e_1 elastogram (SNR, improved by \( \sqrt{N-2} \) and so on, up to one elastogram for Ne_1 (no improvement in the SNR,). Due to this uneven improvement of the SNR, for different strain values, the final strain filter acquires a skewed shape. Most importantly, the softer areas (low strains) will always be shown with a highest SNR, since they will always be more elastograms available for low applied strains. This ultimately means that in the expanded dynamic range elastogram, the softer areas will appear less noisy than the harder areas when averaging is used. Finally, in order to compare the two cases, with and without averaging, we consider the latter as being a subcase of the former. This enables us to define the dynamic range as the width of the composite strain filter at the -6 dB level of the ‘smallest’ strain filter, or the strain filter corresponding to the largest compression. Based on this definition and from figures 7 and 8, it is clear that averaging leaves the dynamic range unaffected. For this reason, averaging was not used in the results to follow.

Figures 9, 10 and 11 correspond to tissue dynamic ranges of 20, 40 and 60 dB, respectively and follow the same pattern where: graph (a) shows the tissue with the ideal sinusoidal strain profile; graph (b) and (c) show the 1D elastogram of that strain profile for an applied strain of 0.1% and 1%, respectively; and graph (d) shows the profile recovered by the dynamic range expansion method.

By comparison of figures 9(a) and 9(b), the application of a single compression of 0.1% proves to be sufficient in the case where DR = 20 dB, since the full sinusoidal form of the actual tissue strain profile is recovered. The strain profile is, however, noisier than the composite one (Fig. 9(d)), since in the case of the latter, the optimal SNR selection method was used. For the cases of 40 and 60 dB (Figs. 10 and 11, respectively), one compression (e.g., of 0.1% or 1%) is not sufficient for imaging the whole tissue dynamic range DR. For purposes of clarity, we have assigned a constant value for the strain for those parts of the elastogram, where the strain estimates are very noisy (low SNR). This constant value is high and low for the soft and hard parts, respectively. It should be noted, however, that in the actual case these estimates are very noisy. Figures 10 (b), 10 (c), 11(b) and 11(c) illustrate that we obtain corrupted strain estimates, if a single elastogram is used. However, figures 10(d) and 11(d) clearly depict the results of expansion, showing that the DR of the composite elastogram covers the entire range of tissue strain values throughout the depth of the tissue.
FIG. 9 Strain vs. depth (mm) for a tissue with DR=20 dB: (a) 1D ideal tissue strain profile; (b) estimated strain profile obtained with one compression of 0.1%; (c) estimated strain profile due to one compression of 1%; and (d) composite strain profile using 20 compressions with a step of 0.1%. Note the expansion of the dynamic range and the similarity between (a) and (d).

The same results are shown in a pseudo-2D fashion in figures 12, 13 and 14. The gray-level scale was fixed at 60 dB dynamic range (black and white depicting hard and soft, respectively), so as to clearly show the whole tissue strain dynamic range in each case. Figure 12 shows how the 20 dB tissue dynamic range has a contrast low enough so as to be recovered by a single compression. Figures 13 and 14 show the effect of recovery of stiffness dynamic ranges by the new technique while a single compression is proven not sufficient.

In figures 15 and 16, we show the results obtained in the case of the 2D simulated phantom containing three circular inclusions of the same size that are 10, 20 and 40 (the ‘blackest’ inclusion) dB harder than the background (E=20 kPa); therefore, the phantom has a total dynamic range of 40 dB. Figure 15(a) shows the ideal strain image calculated at an applied strain of 2%. Figure 15(b) shows the elastogram obtained when compressing by 1%. All three inclusions are visible but the difference in stiffness between the 20 dB and 40 dB inclusions can hardly be distinguished. The reason that we cannot distinguish between the stiffness of these inclusions is because they are not included in the strain filter. There has not been enough strain incurred in those inclusions so that they can strain enough and, thus, have optimally high SNR$_s$. In other words, their difference in strain (or stiffness) cannot be assessed unless their SNR$_s$ are sufficiently high, i.e., included in the optimal region of the strain filter. The black pixels that appear in the highly-soft regions are also excluded from the strain filter range due to decorrelation (peak-hopping errors) associated with high strains. However, when applying the method for the dynamic range expansion (Figs. 15 (c) and (d)), the dynamic range of 40 dB is recovered. This is because the composite strain filter is now broader and can contain both lower and higher tissue strains. The difference in strain between the 20 dB and 40 dB inclusion has also been recovered. In addition, averaging (Fig. 15(d)) significantly improves the SNR$_c$ and, thus, the quality of the composite elastogram.
FIG. 10 Strain vs. depth (mm) for a tissue with DR=40 dB: (a) 1D tissue strain profile; (b) estimated strain profile due to one compression of 0.1%; (c) estimated strain profile of one compression of 1%; and (d) composite strain profile using 20 compressions at a step of 0.1%. Note the expansion of the dynamic range and the similarity between (a) and (d).

FIG. 11 Strain vs. depth (mm) for a tissue with DR=60 dB: (a) 1D tissue strain profile; (b) estimated strain profile by the use of one compression of 0.1%; (c) estimated strain profile with one compression of 1%; and (d) composite strain profile using 20 compressions with a step of 0.1%. Note the expansion of the dynamic range and the similarity between (a) and (d).
FIG. 12 DR=20 dB: (a) Tissue strain pseudo-2D image; (b) estimated strain image by the use of one compression of 0.1%; (c) estimated strain image with one compression of 1%; and (d) composite elastogram using 20 compressions with a step of 0.1%. Note the expansion of the dynamic range and the similarity between (a) and (d).

V. DISCUSSION

The expansion of the dynamic range in elastography implies an increase of the width of the strain filter. This can be achieved in three ways: by modifying the technical parameters defining the strain filter, by using multicompensation or A-line averaging, or by increasing the applied strain dynamic range. However, the dependencies between the technical and the image parameters indicate that their trade-offs would hinder a large expansion of the elastographic dynamic range using the first method. The averaging methods also proved to be very limited in expanding the $DR_e$ (Appendix B).

The method introduced in this paper accomplishes the expansion of the dynamic range by selecting data with the highest $SNR_e$ from a multiplicity of elastograms, each resulting from a different total applied strain. From the results shown in figures 15 and 16, comparing the current elastographic performance with that of the new method, we show that the latter produces elastograms with significantly expanded dynamic range. All results were compared to the ideal case (Fig.15(a)). It should be noted, however, that in the ideal case of the strain image, the finite elements were on the order of a pixel and, therefore, the ideal strain case is only approximated by the finite element model. Furthermore, in the example of figures 15 and 16, we defined a stiffness dynamic range of 40 dB. However, both the ideal and the expanded images show that, due to the boundary conditions set by the three inclusions, a highly-strained artificial area appears on the strain image due to stress concentration. This increases the average strain dynamic range relative to the stiffness dynamic range by 6 dB, as
shown in figure 16. This fact denotes that, besides the stiffness and the applied strain dynamic ranges (Eq. 6), the boundary conditions also play a significant role in determining the tissue strain dynamic range.

The sensitivity (i.e., the minimum estimated strain) of the composite strain filter is also significantly improved. This allows the distinction of the two hardest inclusions in the example of figures 15 and 16. When a single compression is considered, both of these inclusions appear hard but almost equally strained (Fig. 15(b)). The dynamic range expansion method gives a composite elastogram (Fig. 16) with those inclusions experiencing a large difference in strain (by 20 dB) equal to their actual stiffness difference, as defined in the FEA model.

Another important aspect of the technique is that the selective storage process optimizes all SNR_e values in the composite elastogram. As a result, in addition to expanding the DR_e and averaging to increase the SNR_e, it also optimizes the SNR_e of the composite elastogram by only considering the high SNR_e regions of the strain filters. We showed that adding averaging between elastograms corresponding to the same amount of compression (or applied strain) further contributes to an (uneven) SNR_e improvement for the composite elastogram. In addition, it was shown that averaging does not affect the dynamic range expansion. Thus, a better overall performance in both SNR_e and DR_e is obtained. Note the similarity between the ideal image (Fig.15(a)) and the final image (Fig.16(b)).

The optimal step size and the number of steps to be used for the variable applied strain process will differ from tissue to tissue. It is difficult to specify the optimal compression pa-
FIG. 14 DR=60 dB: (a) Tissue strain pseudo-2D image; (b) estimated strain image by the use of one compression of 0.1%; (c) estimated strain image with one compression of 1%; and (d) Composite elastogram using 20 compressions with a step of 0.1%. Note the expansion of the dynamic range and the similarity between (a) and (d).

rameters for each tissue a priori. For example, the first compression of 0.1% might be optimal for a relatively soft tissue, but too small for a harder tissue. Alternatively, a 2% maximum compression might be redundant for a soft target but hardly sufficient for a hard target. This redundancy can be reduced if a nonlinear (e.g., logarithmic) step is used; it will involve the same $\text{DR}_e$ but eliminate the redundant small compression steps. However, the step size and number of compressions cannot be universal. The limit set by the amount of the first compression used can be overcome by using a method combining both rf and envelope data. This is because the envelope decorrelates more slowly than does the rf.

In order to describe the variable applied strain process, we introduced the ripple characteristic, with a minimum at zero and a maximum at the -6 dB level of the strain filter. It depends on the amount required for the $\text{DR}_v$ expansion and the number of variable applied strains used to cover that range. It therefore requires knowledge of $\text{DR}_v$, $\text{DR}_c$, and $\text{DR}_a$. While the last two are easy to determine, the tissue dynamic range is unknown in the practical case. So, the ripple is a theoretical way of describing the performance of this method.

In the 2D case, we showed that the dynamic range can be fully recovered in the case where the tissue has a dynamic range of 40 dB. Furthermore, the difference between inclusions with the same level of hardness but different stiffnesses could also be recovered. This finding indicates that using this method of dynamic range expansion in elastography may help distinguish between benign and malignant tumors, such as fibroadenomas and carcinomas. Both of these tumors are much harder than the normal tissue and have a typical stiffness difference of 10 dB. Unless the dynamic range is expanded, they cannot be distinguished on a
FIG. 15 2D simulation: (a) Ideal strain image and (b) elastogram obtained with a single compression of 1%. The highly strained areas of the ideal strain image are blackened on the elastogram so as to mainly denote peak hopping (i.e. decorrelation) errors. Note that the two hardest inclusions have equal mean strains and, therefore, their difference in stiffness is not apparent.

FIG. 16 2D simulation: (a) DR expanded elastogram obtained by using 8 frames of 0.25% incremental strain and (b) same as (a) but with added averaging. All three inclusions can now be distinguished corresponding to average strains on the order of 0.012%, 0.1% and 0.3% while the average strain of the background is 0.7%. The strain artifact that appears as an extremely soft region has a strain on the order of 2%. This gives an average strain dynamic range of 46 dB, which is higher than the stiffness dynamic range defined in the FEA model.
typical elastogram (Fig.15(b)). In addition, lateral and elevational decorrelations do not seem to have any significant effect on the method. This may be because the strains that are picked to be assembled in the composite elastogram are small enough (<1%) so that the lateral or elevational decorrelation has not become significant. Finally, when averaging is added to the method, the elastographic noise is shown to be further reduced.

APPENDIX A

In elastography, we use crosscorrelation to perform TDE and there are many parameters that affect the precision of this estimate. In order to fully describe their interdependencies as well as their contributions to the TDE, the concept of a strain filter has been introduced. It gives the upper bound of the $SNR_e$ (elastographic signal-to-noise ratio) as a function of the measured tissue strain ($e_e$) and the lower bound of the strain standard deviation ($\sigma_{ZLZ}$):\(^6\)

$$SNR_{e}^{UB} = \frac{e_e}{\sigma_{ZLZ}}$$ \hspace{2cm} (A1)

The strain filter is divided into three operating regions according to the value of the post-integration SNR in the expression for the $\sigma_{ZLZ}$:\(^6, 11\)

$$SNR_{e}^{UB} = \left\{ \begin{array}{ll}
\frac{\pi e_e T^{3/2} \Delta t}{\sqrt{12}} \left[ \frac{B^3}{f_o^2} + 12 \frac{B}{1 + \frac{1}{SNR_5^2}} \right] & \eta < BT \ \text{SNR}_C \\
\frac{\pi e_e T^{3/2} \Delta t}{\sqrt{72}} \left[ \frac{B^5}{f_o^2} + 12 \frac{B^3}{1 + \frac{1}{SNR_5^2}} \right] & \gamma < BT \text{SNR}_C < \eta, \\
\frac{\sqrt{6 T \Delta t}}{T} & \text{BTSNRC} < \gamma
\end{array} \right. $$ \hspace{2cm} (A2)

where we have:\(^6\)

$$\eta = \frac{2}{T \Delta t} \frac{6}{\pi^2} \left( \frac{f_o}{B} \right)^2 \varphi^{-1} \left( \frac{B^2}{24 f_o^2} \right)^2$$

$$\gamma \approx 0.46 \frac{2}{T \Delta t}$$
typical elastogram (Fig. 15(b)). In addition, lateral and elevational decorrelations do not seem to have any significant effect on the method. This may be because the strains that are picked to be assembled in the composite elastogram are small enough (<1%) so that the lateral or elevational decorrelation has not become significant. Finally, when averaging is added to the method, the elastographic noise is shown to be further reduced.

**APPENDIX A**

In elastography, we use crosscorrelation to perform TDE and there are many parameters that affect the precision of this estimate. In order to fully describe their interdependencies as well as their contributions to the TDE, the concept of a strain filter has been introduced.\(^6\) It gives the upper bound of the SNR\(_e\) (elastographic signal-to-noise ratio) as a function of the measured tissue strain (\(\varepsilon_e\)) and the lower bound of the strain standard deviation (\(\sigma_{ZZLB}\)):\(^6\)

\[
SNR_e^{UB} = \frac{\varepsilon_e}{\sigma_{ZZLB}}
\]

(A1)

The strain filter is divided into three operating regions according to the value of the post-integration SNR in the expression for the \(\sigma_{ZZLB}\):\(^6,11\)

\[
SNR_e^{UB} = \begin{cases} 
\pi \varepsilon_e T^{3/2} \Delta t \left[ \left( \frac{B^3 \phi^2 + 12 B}{f_o} \right)^2 - 1 \right]^{1/2}, & \eta < BT \text{ SNR}_C \\
\pi \varepsilon_e T^{3/2} \Delta t \left[ \left( \frac{B^5 \phi^2 + 12 B^3}{f_o} \right)^2 - 1 \right]^{1/2}, & \gamma < BT \text{ SNR}_C < \eta, \\
\frac{\sqrt{6T \Delta t}}{T}, & BT \text{ SNR}_C < \gamma
\end{cases}
\]

(A2)

where we have:\(^6\)

\[
\eta = \frac{2}{T \Delta t} \frac{6}{\pi^2} \left( \frac{f_0}{B} \right)^2 \varphi^{-1} \left( \frac{B^2}{24 f_o^2} \right)^2
\]

\[
\gamma \approx 0.46 \frac{2}{T \Delta t}
\]
with $\eta$ and $\gamma$ being threshold points, $T$ the window size (which is related to the axial resolution$^6$), $\Delta t$ the interval between successive strain estimates, $\varphi^{-1}(y)$ is the inverse of

$$\varphi(y) = \frac{1}{\sqrt{2\pi}} \int_{y}^{\infty} e^{-x^2/2} dx,$$

$f_0$ the center frequency of the transducer, $B$ the equivalent square bandwidth of the transducer, $\rho$ the correlation coefficient and $\text{SNR}_r$ the sonographic signal-to-noise ratio. The first region is Eq. (2) is called the CRLB region, the second is the Barankin region and the third is described as the constant variance region. Also,

$$\frac{1}{\text{SNR}_C} = \frac{1}{\text{SNR}_r} + \frac{1}{\text{SNR}_e}$$

(A3)

where $\text{SNR}_e$ = total signal-to-noise ratio due to sonographic (random, electronic, quantization) and decorrelation noise,$^6$ the latter being given by$^8$

$$\text{SNR}_r = \frac{\rho}{1 - \rho}$$

(A4)

The correlation coefficient $r$ is estimated by its statistical definition:$^9$

$$\rho(t_1, t_2) = \frac{C(t_1, t_2)}{\sqrt{C(t_1, t_1)C(t_2, t_2)}}$$

(A5)

where $C(t_1, t_2)$ is the covariance of one rf line $x(t)$ at times $t_1$ and $t_2$ and $\tau = t_1 - t_2$ is the time-delay. Plotting $\text{SNR}_r$ vs. the measured strain $(\epsilon_r)$ from Eq. (7) provides the theoretical representation of the strain filter (Fig. 2). It is equivalent to a bandpass filter in the strain domain with its width designating the elastographic dynamic range $\text{DR}_{\epsilon}$.$^6$

**APPENDIX B**

In this section, we graphically show the effect of two methods of averaging on the $\text{DR}_{\epsilon}$: multicompression (elastogram) and A-line (sonogram) averaging. Multicompression averaging has been previously used in order to improve the $\text{SNR}_e$$^{11,12,14,17}$ but $\text{DR}_{\epsilon}$ expansion using the same method has not been described. Figure B1(a) shows that multicompression averaging leads to the increase in strain filter amplitude, thereby increasing the sensitivity on the left side of the strain filter. This translates into a lower $\epsilon_{\text{min}}$ in Eq. (1) and to an increase in the $\text{DR}_{\epsilon}$. However, it is important to note that this increase is only on the order of 5 dB.

A-line averaging can be performed by averaging a fixed number of A-lines corresponding to the same amount of compression. This is expected to lead to an increase of the $\text{SNR}_e$ by $\sqrt{N}$ and a subsequent improvement in the $\text{SNR}_e$ according to Eq. (A2). Figure B1(b) depicts the effect of A-line averaging on the $\text{DR}_{\epsilon}$. When $\text{SNR}_e$ is low, $\text{DR}_{\epsilon}$ is very poor and averaging can contribute to a significant $\text{DR}_{\epsilon}$ expansion. On the other hand, when $\text{SNR}_e$ is high, averaging has a negligible effect on the already large $\text{DR}_{\epsilon}$. 
FIG. B1 The strain filter changes with (a) number of multicompression used for averaging: solid: $n=1$, $x$: $n=2$, $o$: $n=4$, and (b) SNR: solid: 10, $x$: 50, $o$: 100. The increase in the DR, due to (a) is almost negligible. There is also an upper limit in the expansion of dynamic range due to (b).
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