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A Novel Performance Descriptor for Ultrasonic Strain Imaging: A Preliminary Study

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Abstract

Ultrasonic strain imaging that uses signals from conventional diagnostic ultrasound systems is capable of showing the contrast of tissue elasticity, which provides new diagnostically valuable information. To assess and improve the diagnostic performance of ultrasonic strain imaging, it is essential to have a quantitative measure of image quality. Moreover, it is useful if the image quality measure is simple to interpret and can be used for visual feedback while scanning and as a training tool for operator performance evaluation.

This report describes the development of a novel quantitative method for systematic performance assessment that is based on the combination of measures of the accuracy of motion tracking and consistency among consecutive strain fields. The accuracy of motion tracking assesses the reliability of strain images. The consistency among consecutive strain images assesses the signal quality in strain images. The clinical implications of the proposed method to differentiate good or poor strain images are discussed. Results of experiments with tissue-mimicking phantoms and *in vivo* breast-tissue data demonstrate that the performance measure is a useful method for automatically rating elasticity image quality.

I. Introduction

The onset of many cancers is accompanied by changes in tissue macrostructure and microstructure that often result in increased tissue stiffness. Unfortunately, many cancers, despite large differences in stiffness, may or may not differ in x-ray attenuation or acoustic properties compared to their surroundings. As a result, many carcinomas are difficult to visualize with standard imaging techniques. For example, approximately 15% of palpable breast cancers are not detectable with mammography, and this number is likely higher in younger women [1]. Ultrasonic strain imaging (E-mode imaging, elasticity imaging, elastography, etc.) is a technique that emulates manual palpation in which tissue is pressed to feel the differences in hardness. Ultrasonic strain imaging has spanned a broad range of applications, including breast tumor detection and differentiation [2], [3], characterization of vascular plaques [4], and assessment of fetal lung maturity [5]. These recent advances suggest that strain imaging provides diagnostically valuable information that is not otherwise available in standard imaging modalities.

Ultrasonic strain imaging uses conventional signals (either radiofrequency or quadrature echo data) from clinical ultrasound scanners acquired before and after deformation is applied and derives relative hardness information—local strains from a displacement function that is estimated by comparing the pre- and postcompression echo fields. General steps in ultrasonic strain-image formation include deforming the imaged tissue using an external or internal

stimulus, measuring tissue response under deformation, and estimating strain from relative tissue motion. Both the complexity and sophistication of ultrasonic strain-imaging systems have increased dramatically over the past 15 years, as summarized in several survey papers [6]–[10]. Alongside this development, there has been a progression in the understanding of strain image quality facilitating the development of predictive theories for the design and enhancement of ultrasonic strain-imaging systems. In early work [11]–[18], attention was focused on estimating lower bounds for displacement estimate error variance, because measuring tissue deformation plays a critical role in strain imaging. A number of authors [11]–[14] have studied the displacement estimate error variance, usually in a simplified form using the formalism and analysis of time-delay estimation (TDE). The general strategy of these approaches has been to seek a closed-form analytical expression, parameterized in terms of ultrasound system configuration (i.e., bandwidth, center frequency, etc.) and time-delay estimation parameters (i.e., window length and window separation). For instance, Carter [11] was among the first to establish the relationship between the Cramer-Rao lower bound (CRLB) for TDE variance and signal magnitude-squared coherence (MSC) $C_{\alpha\beta}(f)$ between signals $\alpha(x)$ and $\beta(x)$. He demonstrated that the Cramer-Rao lower bound σ_{CRLB}^2 is a function of $C_{\alpha\beta}(f)$ as well as the estimation window length T in TDE [11]:

$$\sigma_{\text{CRLB}}^2 = \left| T \int_{-\infty}^{\infty} (2\pi f)^2 \frac{C_{\alpha\beta}(f)}{1 - C_{\alpha\beta}(f)} df \right|^{-1}, \quad (1)$$

$$C_{\alpha\beta}(f) = \left| \frac{S_{\alpha\beta}(f)}{\sqrt{S_{\alpha\alpha}(f)S_{\beta\beta}(f)}} \right|^2, \quad (2)$$

where $S_{\alpha\beta}(f)$ is the cross-power spectral density, $S_{\alpha\alpha}(f)$ and $S_{\beta\beta}(f)$ are the respective auto-power spectral densities, and f is the frequency.

The predicted jitter error is the minimum error achievable by any unbiased time-delay estimation algorithm including, but not limited to, correlation-based algorithms. Walker and Trahey [12] extended Carter's theory to include partially decorrelated signals. However, the CRLB is applicable only when the sonographic signal-to-noise ratio (i.e., the SNR in radiofrequency signals) is high (e.g., > 30 dB); otherwise, the Barankin bound or the Ziv-Zakai bound are more appropriate [13], [14].

In ultrasonic strain imaging, axial strain $\hat{s}$ is often estimated from the difference between two displacement estimates $\hat{D}_1$ and $\hat{D}_2$ that are measured by a window length Z and axially separated by a distance of ΔZ as follows [15]:

$$\hat{s} = \frac{(\hat{D}_2 - \hat{D}_1)}{\Delta Z}. \quad (3)$$

The covariance $\text{Cov}(\hat{D}_1, \hat{D}_2)$ for one-dimensional (1-D) motion tracking can be conservatively approximated by the error variance in displacement estimates σ_d^2 as follows [15]:

$$\text{Cov}(\hat{D}_1, \hat{D}_2) \leq \sigma_d^2 \left(1 - \frac{\Delta Z}{Z}\right). \quad (4)$$

From this result, the lower bound on error variance in estimated axial strain can be obtained by assuming $\sigma_{D_1}^2 \approx \sigma_{D_2}^2 = \sigma_d^2$ for stationary echo signals [15]:

$$\sigma_s^2 = \frac{\sigma_{D_1}^2 + \sigma_{D_2}^2 - \text{Cov}(\hat{D}_1 - \hat{D}_2)}{\Delta Z^2} \geq \frac{2\sigma_d^2}{Z\Delta Z}. \quad (5)$$

Eq. (5) demonstrates that the minimum error achievable in axial strain estimates is predictable, once the strain processing parameters (i.e., window length Z and window separation distance ΔZ) are known. Bilgen and Insana [16], among others, have shown that the error variance of axial strain estimates for small strains (e.g., $< 0.1\%$) increases monotonically with axial strain. However, it is well recognized that such small axial strains result in low contrast strain images [8]. It also is well understood that severe signal decorrelation occurs with large deformation (e.g., strain $> 10\%$) resulting in poor quality strain images [16]–[18]. There is an intermediate range of deformations from which reasonably high quality strain images can be obtained. The error variance bound alone is insufficient for selecting an optimal strain range and that is why the SNR, a relative measure, is of greater interest as a general performance measure.

Varghese and Ophir [17] made use of these error variance bounds to estimate elastographic SNR_e . They defined the elastographic SNR_e as the ratio of the mean value of the estimated strain m and the standard deviation of the estimated strain errors σ_s as follows:

$$\text{SNR}_e = \frac{m}{\sigma_s}. \quad (6)$$

The behavior of SNR_e as a function of axial strain is similar to a bandpass filter; therefore, the analysis result was called a strain filter. Potential performance assessed by the strain filter approach offers insight for designing strain-imaging systems, though the strain filter approach may be applicable only to homogeneous regions of tissue being imaged [17]. For example, the effects of modifying several system parameters (such as the center frequency, bandwidth, and tissue deformation) on the performance of a strain-imaging system can be predicted by the strain filter. In general, high center frequency, broad echo signal bandwidth, and moderately small ($\sim 1\%$) strain are preferred for strain imaging. Similar conclusions were drawn by others using a different approach [16], [18]–[22].

Unfortunately, error variance analysis based on the strain-filter approach is inadequate for several reasons. First, to achieve a closed-form solution, the variance bounds are often derived with simplifying assumptions that limit applicability. For example, error variance bounds for strain imaging were derived for 1-D time-delay estimation problems. However, ultrasonic speckle tracking algorithms can be multidimensional [23]–[25] or noncorrelation based [26], [27]. In addition, the effects of smoothness constraints (i.e., motion regularization [26], [28]) in displacement estimation are difficult to model statistically. Second, variance bounds assume large displacement errors can be detected and corrected so the residual errors in motion tracking are subsample jitter errors. This is a good assumption for some experiments, such as radiation-force experiments [29]–[31] in which deformations are small compared to acoustic wavelength. But experiments in which axial strain is typically 1–2% commonly involve displacements of more than one wavelength. In addition, displacement estimate error variance bounds obtained with homogeneous and isotropic phantoms provide overly optimistic results for *in vivo* biological tissues because motion in biological tissues is far more complex than that in typical phantoms. Third, error variance bounds are used to place a limit on the expected result in any single observation by an unbiased time-delay estimation algorithm. However, in medical-image formation in which accuracy in a single observation is important, variance bounds (descriptions of anticipated image noise) are insufficient to describe the performance for a specific deformation field. In other words, it also is important to have a method that can assess accuracy in each case individually.

Recall that, in ultrasonic strain imaging, the goal of speckle tracking between two radio frequency (RF) echo fields r_A and r_B is to obtain a transformation T that maximizes the similarity between r_A and $T(r_B)$. Thus, strain image quality can be judged, in part, by assessing the motion tracking accuracy directly, as opposed to statistically. An example of this approach is the trashogram [32] that displays the local normalized correlation coefficients between the pre- and postdeformation RF echo fields as a grayscale image. Although this method is attractive due to its simplicity, it can be misleading when displacement errors of an integer wavelength occur. A more comprehensive framework is based on signal coherence between the pre- and motion-compensated postdeformation RF echo signals [33]–[35]. By comparing the cross-power spectrum between the pre- and motion-compensated postdeformation RF echo signals, Insana and Cook [33] and Cook *et al.* [34] derived the Fourier cross-talk matrix to assess ultrasonic strain imaging systems. Basically, motion tracking can be evaluated in terms of spatial sampling characteristics. The Fourier cross-talk matrix, to some extent, can be regarded as a graphical representation of signal coherence. The diagonal elements of the cross-talk matrix represent the generalized transfer function, describing the strength of every Fourier coefficient representing the signals. The off-diagonal components of the cross-talk matrix represent the degree of aliasing between any two Fourier coefficients. If the pre- and motion-compensated postdeformation RF fields are aligned perfectly, no off-diagonal elements will be observed. When motion tracking errors result in signal misalignment, off-diagonal elements in the cross-talk matrix increase. Although the graphical representation of signal coherence makes this method appealing, this approach is most useful in strain imaging system design and is more difficult to use as a performance tool for strain imaging of biological tissues. The trace of the cross-talk matrix was offered as a summary performance measure, but it is an unbounded quantity that would be difficult to interpret in a clinical setting.

We propose a different approach to the performance assessment problem, one that is heuristic in nature. The two components of our strain-imaging performance measure are an assessment of motion tracking accuracy and consistency among consecutive strain fields. The motion tracking accuracy, measured by the normalized correlation coefficient between reference and motion-compensated target RF echo fields, describes the fidelity of displacement estimates from which the strain images are obtained. The consistency among consecutive strain images, measured by the normalized correlation coefficient between consecutive, motion-compensated strain images, relates directly to the SNR in strain images. In the proposed method, both parameters were estimated by a single scalar metric, the normalized correlation coefficient, and an empirical equation then was used to obtain a single summary measure of the overall quality for strain images. Compared to methods available in the literature, the proposed method has several advantages:

- no assumptions are needed regarding the signals, underlying motion, or motion-tracking algorithms;
- performance of strain imaging can be assessed for individual cases accurately;
- the final performance descriptor, a scalar value between zero and one, is quantitative and easy to interpret.

The remainder of this paper is organized as follows. Section II describes performance assessment criteria for ultrasonic strain imaging, as well as implementation details of the proposed algorithm. We then present results of tests of the proposed method with a tissue-mimicking (TM) phantom and *in vivo* breast tissue data including comparisons with ranking of images by human observers, followed by a discussion section and conclusions.

II. Methods and Materials

It is well accepted that local strains correlate strongly with tissue modulus distribution under certain boundary conditions (e.g., uniaxial compression) [36], [37]. When full knowledge of the ground truth (the modulus distribution and boundary conditions) is available (i.e., a numerically simulated or tissue-mimicking phantom), a comparison of an estimated strain field to the ideal strain field provides an ideal basis for error analysis. In fact, some authors [38], [39] have used this approach to validate new algorithms. Unfortunately, true modulus maps are unavailable a priori for *in vivo* biological tissues, noting that acoustic scattering and tissue elasticity are uncorrelated [40]. There is a need for a method that would allow the evaluation of strain-image quality when the ground truth is not available.

Two important aspects of ultrasonic strain imaging, namely motion tracking accuracy and consistency among consecutive strain images, were used in several papers [2], [32] as measures of strain-image quality. Hall *et al.* [2] argued that examining tissue motion through a relatively long (> 10 frames) sequence of B-mode images, together with consistency among successive strain images, would provide some assessment of confidence in strain-image accuracy. Kaluzynski *et al.* [32] used the RF signal correlation value of 0.985 as a measure for strain-rate imaging and stated that reliable motion tracking would not be guaranteed if the correlation value fell below 0.985. The work presented below combines motion tracking accuracy and the consistency among consecutive strain images to create a performance-assessment method that automatically quantifies strain image quality on a normalized scale.

The normalized cross correlation (NCC) between the two fields is a common measure of their similarity. Because frame-average tissue deformations of 1% strain are easily achieved *in vivo*, and local deformations can approach 5% strain, comparisons are made between a reference field, α_{ij} , and the motion-compensated target field, $T(\beta_{ij})$. Thus, the NCC, $\rho_{\alpha\beta}$, can be written as follows [41]:

$$\rho_{\alpha\beta} = \frac{\sum_{i=1}^M \sum_{j=1}^M (\alpha_{ij})(T(\beta_{ij}))}{\sqrt{\sum_{i=1}^N \sum_{j=1}^M (\alpha_{ij})^2} \sqrt{\sum_{i=1}^N \sum_{j=1}^M (T(\beta_{ij}))^2}}, \quad (7)$$

where N and M are the width and height of the frames of data, respectively.

A. Motion Tracking Accuracy

As stated above, a goal of ultrasonic strain imaging is to obtain a transformation T that maximizes the similarity between two RF echo fields rf_{n-1} and $T(rf_n)$. Local displacement and strain are estimated from this transformation. Once the local displacements are known, the target field can be resampled (e.g., using a cubic spline interpolation algorithm) to obtain its corresponding motion-compensated target field. Thus, the accuracy of motion tracking can be quantified by the normalized cross correlation, ρ_{rf} , between the reference RF echo field rf_{n-1} and the motion-compensated target RF echo field, $T(rf_n)$.

B. Consistency Among Strain Images

Similarly, the consistency among strain images can be defined by the normalized cross correlation, ρ_s , between the previous strain field s_{n-1} in a sequence of consecutive fields and the current strain field in the sequence s_n mapped into the spatial coordinate system of strain field s_{n-1} .

For small deformations, the strain information in successive images have approximately the same underlying signal (i.e., the tissue modulus distribution), but the signals are corrupted by noise. Belaid *et al.* [42] have shown through simulations that noise in strain fields estimated RF echo signals is Gaussian distributed. Given the assumption that noise in strain images is uncorrelated with its underlying signal, a high correlation between two consecutive, motion-compensated strain images means relatively low noise in both strain images, and thereby suggests better strain image quality.

C. Empirical Equation

Correlation among motion-compensated RF echo fields and strain images are both important measures of strain imaging system performance. Combining them to provide a single summary performance measure for the overall quality of ultrasonic strain imaging is a logical approach, and a simple empirical equation for this combination is:

$$P = \rho_{rf} \rho_s, \quad (8)$$

where p is the overall performance. It is worth noting that the summary performance measure p ranges from zero to one.

D. Implementation

We implemented the proposed summary performance measure in our existing strain-image formation software in MATLAB® (Mathworks Inc., Natick, MA), as schematically illustrated in Fig. 1. The proposed method consists of following major steps:

- Obtain a pair of RF frames (e.g., the $(i-1)$ th and (i) th frame in Fig. 1 in which the (i) th frame is the reference frame) and track motion. The displacement field contains both lateral and axial displacement components from the (i) th frame to the $(i-1)$ th frame. Form a strain image in the coordinate system of (i) th RF echo frame (e.g., S_i in Fig. 1).
- Use the displacement field obtained in step 1 to warp the (i) th RF echo frame into the $(i-1)$ th coordinate system and calculate the normalized cross correlation between the $(i-1)$ and motion-compensated (i) th RF echo field to assess the motion tracking accuracy. Note that warping is a process of compensating the motion between the (i) th and the $(i-1)$ th strain frames, as described in Section II-A.
- Warp the (i) th strain image into the $(i-1)$ th coordinate system and calculate the normalized cross correlation between the $(i-1)$ th and motion-compensated (i) th strain images to estimate the consistency between consecutive strain images. Note that the $(i-1)$ th strain image is formed at the physical grid of the $(i-1)$ th RF echo field.
- Calculate the summary performance measure (8) and assign this value to the (i) th strain image.
- Repeat step 1–4 for each pair of RF echo frames in a sequence.

E. Remarks

The proposed method performs best in a sequence of strain images in which the estimated performance values are slowly varying. The success of ultrasonic strain imaging relies on the ability to control tissue motion during deformation. For instance, the ideal motion for breast scanning is a nearly uniaxial compression, with minimal out-of-plane motion [2]. To maintain consistency between two successive strain images, the boundary conditions and modulus distribution that is being imaged have to be nearly unaltered during data acquisition. Real-time

elasticity imaging systems [2], [25] that provide elasticity images with a frame rate high enough to control the boundary conditions of free-hand deformation result in consistently high-quality, elasticity images. To a first approximation, the elastic moduli of biological tissue are constant for small deformations [43]. Also, with a sufficiently high frame rate between the RF echo frames paired to form strain images, the viscosity of biological tissue may be ignored [44].

There are at least two reasonable approaches to estimating consistency among strain images that relate to the selection of a reference strain image. One may choose the best quality strain image among the sequence as the standard for comparison (the reference strain-image approach). A second approach is to use the adjacent strain image as the standard for comparison. There are several motivations for using the adjacent strain image approach over the reference strain image approach. First, the selection of the best strain image is likely subjective and not fully automated. The adjacent strain image approach provides full automation, thereby suggesting an objective assessment. Second, the assumptions that the modulus distribution and boundary conditions are unaltered may be problematic if a single reference strain image in a long sequence of data (typically greater than 60 RF echo frames) is used. It is easy to argue that these assumptions are valid for adjacent strain images in which small deformation increments (1% strain) under similar boundary conditions are applied to the object being imaged.

One drawback of using the adjacent strain image approach is that comparison of a high-quality strain image with a low-quality strain image will result in degraded cross correlation. It is possible to reassign a higher consistency value to the (i)th strain image when it correlates poorly to a low-quality ($i - 1$)th frame, but correlates well with the ($i + 1$)th strain image. The scheme does not work when a reasonably high-quality strain image is interleaved between two low-quality strain images. Although the reference strain image approach might work well in that case, the subjectivity in reference frame selection, the loss of automation, and the potential for violating the assumption regarding unaltered boundary conditions make that approach significantly less attractive.

III. Algorithm Evaluation

The proposed method for quantifying strain image quality was tested with RF echo data acquired from a TM phantom and *in vivo* breast tissue. The first test of the proposed method used a TM phantom with a known elasticity distribution and its corresponding strain image under well controlled imaging conditions. The second test evaluated algorithm performance using *in vivo* breast tissue data acquired with free-hand scanning. Image ratings obtained from three human observers were compared with measured performance values to determine whether results from the proposed method match well with human perception.

A real-time, strain-imaging system [2], [25] based on the Siemens SONOLINE Elegra (Siemens Medical Solutions, Mountain View, CA) with a 7.5 MHz linear array (7.5L40) transmitting 7.2 MHz broadband pulses was used to guide in-phase and quadrature (I-Q) data acquisition. The strain images used in this study were processed off-line by first converting the I-Q data to RF, then forming strain images using a more numerically demanding algorithm [45] than the real-time algorithm on the Elegra [25]. This motion-tracking algorithm is a modified block matching algorithm and consists of the 2-D search for equivalent patterns between pre- and postdeformation RF echo fields delimited by a small, 2-D kernel. The sum-squared-difference (SSD) is used to estimate displacement fields. A small, 2-D nonoverlapping kernel 0.96×0.40 mm (length by width) was used to track tissue motion. Displacement estimates in a small, 1-D window then were fitted into a line locally, and the slope of this line was assigned to the center of this window as the estimated local strain value. In this study, a relatively large window (2.4 mm) was used to obtain axial strains that were displayed as

grayscale images. No additional filtering was applied in this study. The performance assessment algorithm has been integrated into our off-line strain-imaging processing program to obtain performance values for all examples shown here.

A. Tissue-Mimicking Phantom Experiment

The tissue-mimicking phantom, shown in Fig. 2, has a uniform background and two spherical inclusions, whose diameters are 2.4 mm and 3 mm, have similar acoustic properties but are three times stiffer than the background. The inclusions are barely visible in B-mode images. The phantom (Fig. 2) was manufactured as described in [40]. Thirty-one I-Q echo frames of data were recorded while free-hand scanning the phantom with the Elegra. The physical size of B-mode images is roughly 38 mm $\times$ 40 mm (W $\times$ L) and a single transmit focal zone was centered at the depth of 20 mm. Note that the reference RF echo frame was paired with frames with different time delays to obtain the six frame-average strains shown in Fig. 2.

B. In Vivo Breast Tissue Experiment

Human subjects who, with informed consent, agreed to participate in elasticity-imaging research were scanned at Charing Cross Hospital, London, UK, and Mayo Clinic (Rochester, MN) using identical Siemens SONOLINE Elegra systems equipped with real-time elasticity imaging software [2], including the linear array ultrasound transducer. Sixty-five frames of RF echo data were acquired from a fibroadenoma, and 99 frames of RF echo data were acquired from an invasive ductal carcinoma.

C. Human Observer Study

Three ultrasound physicists who are actively involved in elasticity-imaging research participated in this human observer study. The observers learned to rate strain images in an initial training session with 100 strain images (10 consecutive strain images from 10 different data sets) that included both benign and malignant solid tumors [five fibroadenoma (FA) and five invasive ductal carcinoma (IDC)]. Observers were instructed to rate the quality of strain images using the scale and criteria shown in Table I. During the training session, the computer ratings for each of the 100 images were provided as feedback to enable all observers to consistently rate strain-image quality.

During the human observer study, 20 different data sets (nine FA, eight IDC, one invasive lobular cancer, one unknown cancer, and one fat necrosis) of *in vivo* breast tissue data were used, and each set consists of at least 60 consecutive strain images. Observers first viewed the complete sequence of side-by-side, B-mode and strain images in each data set, then rated the quality of the predetermined subset of 10 strain images for that data set. Computer ratings of these 200 strain images were unknown to the observers. By first viewing the complete data set, observers learned the typical appearance of the specific lesion in that data set. Scoring 10 successive strain frames reduced the number of strain images that must be rated by observers in order to achieve a statistically significant result.

Specific instructions were given to observers on how to determine image quality. The approximate location and contour of the lesion in the sequence of B-mode images was used to set expectations of lesion size and location in strain images. Lesion location in strain images must correspond to that in B-mode, but size and contrast in the two image types can differ significantly. No attempt to compare lesion morphology was suggested to the observers. The observers may try to identify the best strain image in a particular sequence, together with adjacent strain images, as the reference image to assess image quality. Note that the reference strain image is not necessary within the span of 10 predetermined strain images. The observers may take complexity of tissue motion into consideration. That is, tissue motion may be visually tracked in a sequence of B-mode images to determine the degree to which RF echo data

decorrelates to subjectively assess the complexity in motion tracking. The image formation algorithm and display grayscale mapping was consistent among all data. Also, no ground truth regarding the correct strain image is available. Therefore, an apparent lack of detail in an image (e.g., image smoothness or lesion contrast) should not bias the observer toward good or bad image quality.

The observers also were asked to follow the same procedures and score a continuous sequence of 40 strain images acquired from a patient with a fibroadenoma. Note that results of this data set from the first 200 strain images will be presented later in this paper. It also is worth noting that all *in vivo* data presented in this subsection was acquired using the real-time, elasticity-imaging system described previously.

A viewing software program providing strain images displayed side-by-side with their corresponding B-mode images was used for this study. Observers could view image sequences at eight frames per second, or slower, or could step through images frame by frame. Image rating was performed only when stepping through the sequence frame by frame. All images were displayed on typical flat panel monitors (NEC MultiSync LCD 1860NX, NEC-Mitsubishi Inc., Japan), and viewing time was not limited. Note that monitors were set to the same configurations.

IV. Results

Representative strain images obtained from the tissue-mimicking phantom experiment are displayed in Figs. 2(a)–(f). The frame-average axial strain varies from 0.3%–4.5%. In each plot, the size of the echo field was 38 mm × 40 mm (width × depth). Note that low-frequency banding is apparent in low-strain images (e.g., < 1.0%). This banding is due, in part, to a biased interpolation algorithm used for obtaining subsample displacement estimates [46]. One measure of image content is the contrast-to-noise ratio (CNR) defined [47] as:

$$\text{CNR} = \frac{2(s_t - s_b)^2}{(\sigma_t^2 + \sigma_b^2)}, \quad (9)$$

where s and σ^2 denote signals and variances of signals, and subscripts b and t represent the background and target, respectively. The estimated CNR for the two spherical targets (CNR₂₄ for the 2.4 mm sphere; CNR₃ for the 3 mm sphere) in strain images together with their estimated performance values (8) are shown in Table II. The estimated CNR correlates with the performance values obtained by the proposed method.

The NCC among motion-compensated RF echo fields, ρ_{rf} , decreases monotonically with the increasing axial deformation, as shown in Fig. 3(a). Note that, given a long sequence of RF data, different frame-average axial strains can be achieved by pairing the pre- and postdeformation RF echo frames separated by different time intervals. It is significant to note that the estimated ρ_{rf} will change somewhat if different regions of interest are used. The consistency of estimated strain images, ρ_s , versus axial compressions is displayed in Fig. 3(b). The horizontal banding artifact shown in Fig. 2 is mitigated as the axial deformation increases, resulting in strain images with less noise and greater consistency from frame to frame. Thus, the estimated consistency among strain images correlates with the CNR of strain images. The estimated summary performance measure as a function of frame-average strain is shown in Fig. 3(c). The estimated performance is consistent with findings reported by Chaturvedi *et al.* [23], which showed that strain image quality (the CNR) increases with frame-average strain up to about 5% for a tissue-mimicking phantom. The error bars in these plots denote one standard error and were obtained from more than 20 pairs of RF and strain fields.

Representative strain images obtained from *in vivo* breast tissue with different axial deformations are shown in Figs. 4(a)–(d). The frame-average axial strain in these images varies from 0.4%–3.0%. The strain-image contrast increases with deformation, and the maximum CNR is obtained when the frame-average axial strain reaches about 2%. Summary performance values correlate with strain image CNR as shown in Table III, thereby suggesting that the estimated performance values are reasonable measures of strain-image quality, similar to the results obtained from the TM phantom experiment.

The correlation among motion-compensated RF echo fields, ρ_{rf} , is plotted with respect to different axial deformation in Fig. 5(a) for the same *in vivo* breast tissue data set represented in Fig. 4. Different frame-average, axial strains were achieved again by pairing the pre- and post-deformation RF echo frames separated by different time intervals. The error bars in Fig. 5 also denote one standard error and were obtained from more than 30 independent pairs of RF and strain fields. The correlation among motion-compensated RF echo fields decreases much faster with increased axial deformation compared to that found in the tissue-mimicking phantom results. This result implies that complex tissue motion is challenging to track with a simple, block-matching algorithm, whereas motion in the TM phantom is relatively uniform and easy to track even under large deformation. The normalized correlation coefficient among consecutive motion-compensated strain images versus frame-average axial strain is plotted in Fig. 5(b). The peak correlation coefficient occurs near 1.2% axial strain. The maximum correlation and the strain at which it is found are much lower than that of the TM phantom experiment. In addition, the correlation falls rapidly beyond the peak value. The estimated performance, shown in Fig. 5(c), is low for small axial deformation and reaches its peak when the frame-average strain is about 0.8% to 1.2%.

During free-hand scanning, a sinusoidal compress/release cyclic deformation was used, and the acquired data typically contained one or more cycles. More details regarding data acquisition can be found in [2]. Unfortunately, free-hand scanning sometimes results in nonuniform, frame-average strains, as illustrated in Fig. 6(a). Adaptively selecting the RF frame pairs in postprocessing [45], [48] to obtain nominally 1–1.5% absolute frame-average strain significantly improves the quality of a sequence of strain images, as demonstrated in Fig. 6(b).

Fig. 7(a) is a typical good quality strain image of an invasive ductal carcinoma. The normalized cross-correlation values for estimating motion-tracking accuracy (ρ_{rf}) and strain-image consistency (ρ_s) were 0.83 and 0.89, respectively. Thus, this strain image was obtained from reasonably accurate displacement estimation and correlated well with its adjacent strain images. An atypical strain image obtained from this data set is shown in Fig. 7(b). The estimated consistency (ρ_s) was 0.81, and therefore it was fairly consistent with its adjacent strain images. But the estimated motion-tracking accuracy ρ_{rf} was 0.47 for this particular strain image. The sequence of B-mode images showed high decorrelation for relatively small axial strain, suggesting extensive elevation (out of acoustic imaging plane) motion.

Fig. 8 shows a plot of the strain image quality rated by human observers (1–10 scale) and the summary performance measure (0–1 scale). Results in Fig. 8 show that the rating by observers was generally well described as a linear function of the summary performance measure ($r = 0.87$). The quality rating by human observers has higher correlation to those by the summary performance measure when the strain-image quality is reasonably high. By filtering the data in Fig. 8 to include only those strain images with a summary performance measure in excess of 0.6 the correlation between human rating and summary performance measure increased to 0.99.

The comparison of average scores of the observers and the summary performance measure based on a sequence of containing 40 consecutive strain images of a fibroadenoma is shown in Fig. 9(a). The frame-average strains are plotted with respect to the frame numbers in Fig. 9(b). All 40 frames of strain data can be seen in Movie 1 (). Note that computer ratings were rescaled from 1–10 for comparison with human rating (Table I). Results in Fig. 9(a) suggest that human rating of strain images was well described by the computed performance values through most of the sequence. However, beyond the 26th frame there are discrepancies between the human observers and the computed performance measure. Observations from the 27th and 28th frames of strain data (Movie 1) show that these two strain images were significantly different compared to typical good strain images in this sequence; therefore, human observers rated these frames low. Adjacent strain image frames were sufficiently similar for the algorithm to rate them reasonably high. In the last 10 frames (31–40) of strain data in Movie 1 (), there was extensive lateral motion, as observed in the B-mode image sequence. Correspondingly, there are signs of motion tracking failure in the strain image sequence and the estimated values of the motion tracking accuracy are relatively low [see Fig. 9(a)]. These 10 strain images are still fairly consistent with typical good strain images in this sequence. It appears that the observers weighted ratings toward consistency of strain images in this particular case [the solid line marked with triangles in Fig. 9(a)]. For these few images, the observers' rating scores match better with the measure of consistency among successive strain images than with the overall performance assessment. It is worth noting that there are large discrepancies between the estimated values of motion tracking accuracy (i.e., ρ_{rf}) and the human ranked values, particularly from the 20th frame to 30th frame as shown in Fig. 9(a). As illustrated by Fig. 9(b), the frame-average strains are low (within $\pm 0.5\%$) from the 20th frame to the 30th frame demonstrating that the motion tracking accuracy is biased toward small deformations.

V. Discussion

In this study, motion tracking accuracy and similarity of consecutive strain images were shown to contribute to the overall quality of strain images. The implication of (8) is that we favor strain images which are consistent with their adjacent peers and are computed from reliable motion estimates. In addition, the particular combination clearly reflects the following facts. Correlation among consecutive RF echo fields, ρ_{rf} , favors small deformations [$\text{abs}(\text{strain}) < 0.5\%$], as illustrated in Figs. 3(a) and 5(a). At the same time, small deformation often results in noisy strain images [see Figs. 2(a) and 4(a)] for which the correlation between consecutive strain images, ρ_s , is penalized. As a result, the product of ρ_{rf} and ρ_s is low at small deformation. However, under large deformation [$\text{abs}(\text{strain}) > 10\%$], the performance value also is low. Large deformation produces large echo signal decorrelation resulting in low ρ_{rf} and ρ_s . Therefore, there is an intermediate range of deformation for which both ρ_{rf} and ρ_s are reasonably high, and good quality strain images can be obtained.

It is interesting to note that pairs of consecutive strain images which are reasonably consistent were found even when echo signals were severely decorrelated, suggesting that strain image consistency as a single criterion can be misleading as a measure of image content and quality. Data presented in Fig. 7(b) are an example. However, using motion tracking accuracy alone to indicate strain-image quality could be misleading too. Figs. 3(a) and 5(a) demonstrate that the normalized cross correlation between a pair of motion-compensated RF echo data is highest for small deformation, but this measure alone also is insufficient to describe the quality of strain images [see Figs. 2(a) and 4(a)]. The results presented in Fig. 8 also clearly show that there are large discrepancies between the estimated motion-tracking accuracy ρ_{rf} and the visual perception of human observers (Movie 3). In summary, the combination of motion tracking accuracy and consistency between consecutive strain images provides a practical solution to objectively rating strain images, though this combination [i.e., (8)] is established intuitively,

and this approach cannot quantify the true, task-dependent psychophysical strain-image quality. In other words, this study showed that the combination of motion tracking accuracy and consistency between consecutive strain images is adequate to assess strain-image quality in the absence of ground truth by applying the proposed method to *in vivo* tissue data in which tissue motion is complex.

Considerably higher summary performance measures were obtained in TM phantom experiments compared to *in vivo* breast tissues. In addition, summary performance measures remained high at large axial strain (e.g., 4.0%) for the TM phantom experiment but decreased significantly beyond about 1.5% frame-average strain for *in vivo* breast tissues. These results suggest that studies involving simulations and phantoms might be overly optimistic for predicting the overall performance of an elasticity imaging system and might be misleading regarding the desirable strain range for image formation. Our algorithm [25] is a modified version of classic block-matching algorithm that assumes rigid body motion. The algorithm does not accurately track large deformation ($> 10\%$ strain), small scale tissue rotation, or shear. Complex tissue motion (e.g., shearing and slipping boundaries in tissue) can cause difficulty in obtaining consistent tissue elasticity images and more robust motion tracking algorithms [26], [27], [49] may be beneficial.

One of the most promising uses of the proposed performance assessment method is to eliminate poor quality strain images from a sequence of images. That is, only the strain images that are consistent from frame to frame and obtained through accurate motion tracking would be included for clinical diagnosis. The visual impression of the tissue elasticity is improved by selecting a threshold (0.65 for the sequence containing 40 strain images in Fig. 9) and including only those strain images whose summary performance measure exceeds that threshold. An unedited sequence of 40 frames of strain images is available in Movie 1 (), and the edited version is available in Movie 2 (). The contour of the *in vivo* fibroadenoma is more consistent throughout the sequence, after low-quality strain images are eliminated.

It also is interesting to note that the observers seemed to heavily weight the consistency of consecutive strain images. This may suggest that, for an algorithm to match the performance of human observers, motion tracking accuracy and consistency among successive strain images might need to be weighted differently. However, the current study is limited by the small number of data sets (10 human subjects) and the involvement of only three observers. A larger number of *in vivo* data sets and observers are essential to reach such a conclusion with statistical significance.

Alternatively, it is not clear that matching the performance of human observers is a necessary goal. The motivation in this work was to aid the observer in determining which images in a sequence could be trusted as displaying accurate elasticity information. Accuracy in tracking motion and consistency in consecutive strain images suggest that a strain image displays accurate information. The summary performance measure based on these parameters is not dependent on what an observer expects or wants to see.

Clinically, the quality of strain imaging is evaluated in terms of displayed strain images, if human observers (typically radiologists) are involved. That is, the human observer is the final arbiter for an elasticity imaging device whose output is intended for clinical diagnosis. It is well recognized that human perception is a complex mixture of psychology, physiology, and environment. The results shown here demonstrate that the summary performance measure correlates well with assessment by human observers, particularly for high-quality strain images. Given that we are most interested in identifying good-quality strain images, the proposed method appears very practical.

In addition to diagnostics, training clinicians is necessary to promote and improve the use of ultrasonic elasticity imaging. The proposed summary performance measure can help trainees understand the importance of maintaining boundary conditions during patient scanning. For instance, the summary performance measure can provide instant feedback to trainees through a scoring system to help them master boundary condition control and through this improve their elasticity-imaging technique and overall image quality.

It is worthwhile to note that the normalized cross correlation is mathematically restricted to stationary random signals. Strain images directly correlate to intrinsic mechanical properties of tissue being imaged, and those properties may not be stationary. RF echo frames of data also may be nonstationary due, in part, to diffraction and frequency-dependent attenuation. In this circumstance, using the normalized cross correlation merely measures pattern similarity. Nevertheless, the correlation value, primarily used for estimating the similarity between two different signals, may be satisfactory as long as this metric provides sufficient differentiability between good or poor performance.

The risk of local recurrence of breast cancer is reduced by removing the tumor and a tumor-negative margin around it. Once a diagnosis of breast cancer has been made, the extent of disease (e.g., lesion boundaries) must be assessed for treatment planning. Preliminary studies [2], [50] have demonstrated that the size of a breast tumor is larger in strain images than shown in B-mode ultrasound images, and it is a reasonable hypothesis that the tumor size in strain images is a more accurate representation of that measured at pathology than that available in B-mode images [2], [51]. Although real-time ultrasonic strain imaging systems [2], [52] are essential for manipulation of boundary conditions to achieve good quality of strain images, quality fluctuations in strain images still exist, as demonstrated by error bars in Fig. 5(c). Objective elimination of low-quality strain images by the proposed summary performance measure makes a sequence of strain images more consistent for tracking lesion boundaries. Therefore, it is reasonable to hypothesize that elasticity imaging and the proposed summary performance measure will improve treatment planning.

The work reported is only part of the assessment of strain-image quality. Other parameters (e.g., resolution) must be incorporated to provide a more comprehensive measure of elasticity image quality. Research is underway to include more attributes of strain-imaging systems to provide more comprehensive assessment of ultrasonic strain imaging.

VI. Conclusions

A quantitative summary performance measure of ultrasonic strain imaging was obtained by combining the measures of motion tracking accuracy and consistency among consecutive strain images. The proposed method can be used to assess the quality of strain images with full automation, and the measured performance is consistent with visual perception. The descriptor can be used clinically as a method for objectively deciding what are good and better strain images and can be used as a training tool providing feedback to the clinician while they scan and learn to obtain high-quality elasticity images. This task is important because the right answer is unknown when heterogeneous tissues are being imaged.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Fig. 1.

A schematic of the frame pairing procedure for strain image formation.

Fig. 2. B-mode and strain images obtained under different axial compression: (a) 0.3%; (b) 0.6%; (c) 1.1%; (d) 2.0%; (e) 3.8%; (f) 4.5%. The white boxes in the B-mode images define the regions of interest from which strain images were estimated.

Fig. 3. Estimates of the NCC between predeformation and motion-compensated postdeformation. (a) RF echo fields. (b) Consecutive strain images. (c) The summary performance values versus axial deformation using the tissue-mimicking phantom. Error bars denote one standard error.

Fig. 4. B-mode and strain images from an *in vivo* breast fibroadenomas at (a) 0.4%, (b) 1%, (c) 2%, and (d) 3% frame-average axial strain. The white boxes in the B-mode images define the regions of interest from which strain images were estimated.

Fig. 5. Estimates of normalized cross correlation between predeformation and motion-compensated, postdeformation. (a) RF echo fields. (b) Consecutive strain images. (c) Performance values versus axial deformation using data acquired from a palpable *in vivo* breast fibroadenoma. Error bars denote one standard error.

Fig. 6.

Plots of (a) the frame-average strain obtained with free-hand scanning of an *in vivo* breast, and (b) the estimated overall performance values. The solid line represents results obtained by pairing adjacent RF frames of data for calculating local strains. The dashed line represents results obtained by adaptively selecting the RF frame pairs to achieve approximately 1–1.5% frame-average strain.

Fig. 7.

B-mode and strain images obtained from an *in vivo* invasive ductal carcinoma. Images in (a) show a typical good-quality strain image and in (b) show a low-quality strain image that is consistent with its adjacent strain images, but it is not consistent with typical good quality strain images in the same sequence. The frame-average strains are 0.92% in (a) and 1.2% in (b), respectively. The estimated summary measures are 0.74 in (a) and 0.38 in (b), respectively.

Fig. 8.

A plot of comparing the summary performance values and human rating scores for 200 strain images. The solid line represents a linear fit between the summary performance measure and human rating scores.

Fig. 9.

Plots comparing (a) the summary performance measure and human rating scores from a sequence of 40 consecutive strain images of a palpable *in vivo* fibroadenoma, and (b) the frame-average strains in the same sequence.

Fig. 10.

A sequence of strain images whose performance scores are plotted in Fig. 8. Movie 1 is the unedited sequence and Movie 2 is the edited sequence in which bad quality strain images whose estimated performance values are below 0.65 are eliminated. Movie 3 is obtained by filtering strain images with an estimated value of motion tracking accuracy (ρ_{rf}) below 0.9.

TABLE I

Guidelines for Rating Strain Image Quality.

Scores	Description
1	Strain images that appear noisy and apparently contain no tissue-elasticity information.
2–3	Strain images that have low CNR but contain no obvious motion tracking failures; or strain images that contain a little tissue-elasticity information and in which noise is so distracting that little useful information can be effectively extracted.
4	Strain images that have some correlation to the reference strain images but noise is apparent; or strain images that are reasonably consistent from frame to frame but have large motion tracking errors that may degrade the ability to extract lesion contours.
5	Strain images that are reasonably consistent from frame to frame and any large motion tracking errors have limited affect on the ability to extract consistent lesion contours.
6–7	Strain images that are consistent from frame to frame and have no significant motion tracking errors.
8–9	Strain images that are not only consistent from frame to frame coarsely, but also preserve structural details reasonably well.
10	Strain images that consistently preserve structural details at a very fine level.

TABLE II

Comparison of Estimated CNR to the Calculated Performance Values in a Tissue-Mimicking Phantom.

	Fig. 2(a)	Fig. 2(b)	Fig. 2(c)	Fig. 2(d)	Fig. 2(e)	Fig. 2(f)
CNR _{2,4}	1.2	4.1	3.7	5.7	6.9	7.9
CNR ₃	3.2	5.4	5.9	8.4	9.3	10.3
Performance value	0.25	0.45	0.65	0.85	0.92	0.93
Frame-average strain	0.30%	0.60%	1.10%	2.00%	3.80%	4.50%

TABLE III

Comparison of Estimated CNR to the Calculated Performance Values for an In Vivo Fibroadenoma.

	Fig. 4(a)	Fig. 4(b)	Fig. 4(c)	Fig. 4(d)
CNR	3.4	12.5	13.5	6.5
Performance value	0.4	0.76	0.82	0.62
Frame-average strain	0.40%	1.00%	2.00%	3.00%