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Lesion edge preserved direct average strain estimation for ultrasound elasticity imaging

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ABSTRACT

Elasticity imaging techniques with built-in or regularization-based smoothing feature for ensuring strain continuity are not intelligent enough to prevent distortion or lesion edge blurring while smoothing. This paper proposes a novel approach with built-in lesion edge preservation technique for high quality direct average strain imaging. An edge detection scheme, typically used in diffusion filtering is modified here for lesion edge detection. Based on the extracted edge information, lesion edges are preserved by modifying the strain determining cost function in the direct-average-strain-estimation (DASE) method. The proposed algorithm demonstrates approximately 3.42–4.25 dB improvement in terms of edge-mean-square-error (EMSE) than the other reported regularized or average strain estimation techniques in finite-element-modeling (FEM) simulation with almost no sacrifice in elastographic-signal-to-noise-ratio (SNRe) and elastographic-contrast-to-noise-ratio (CNRe) metrics. The efficacy of the proposed algorithm is also tested for the experimental phantom data and *in vivo* breast data. The results reveal that the proposed method can generate a high quality strain image delineating the lesion edge more clearly than the other reported strain estimation techniques that have been designed to ensure strain continuity. The computational cost, however, is little higher for the proposed method than the simpler DASE and considerably higher than that of the 2D analytic minimization (AM2D) method.

1. Introduction

Elastography is an emerging medical imaging modality for detecting the abnormal changes in soft tissue via the assessment of tissue stiffness usually in terms of strain. It can be considered an alternative to manual palpation of tissue, practiced by physicians for primary clinical diagnosis. Generally, pathologic and stiffness changes in soft tissue are well-correlated, and therefore, abnormal changes in stiffness convey warning signs of diseases in organs like breast, liver, and prostate [9,17,18]. In quasi-static elastography, various strain estimation methods have been developed for the detection and classification of lesions and/or tissue pathology change. Some of them are gradient-based techniques [1,8,15,17,18,25] where the strain is typically computed as the spatial gradient of local tissue displacements, and some are direct-strain-estimation techniques [3,16,23] where the strain is directly estimated from the pre- and post-compression RF echo waveforms or spectra.

The gradient-based strain estimators face challenges in maintaining displacement continuity due to pre- and post-compression echo decorrelation, and other noise artifacts [3,8,16]. The gradient operation over the displacement map further amplifies these high frequency noise while estimating strain [1,23]. To obtain a noise reduced strain map, a smoothing technique based on least-squares-linear-regression [13] or least-squared-error-based smoothing-spline [1] can be applied on the displacement matrix before the gradient operation. In addition, some of the recent methods designed to ensure displacement continuity (and thus strain continuity) use estimates from the previous window in estimating the interrogated window displacement [20–22,25]. In all these techniques, strain continuity is achieved only at the cost of lesion edge blurring along with the smoothing of the natural stiffness variation inside the lesion.

Noise in the strain map resulting from the derivative operation in the gradient-based methods can be avoided by using direct-strain-estimation methods that exist both in the time [3,11] and frequency domain [10,23]. Though these methods show better

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SNRe performance than the gradient-based techniques, they also face challenges to ensure strain continuity among neighborhood due to echo decorrelation. To ensure strain continuity, in [10,11], a cost function is defined for an interrogated point on the strain map from its exponentially weighted neighboring window pre- and post-compression RF spectral sum-of-square-differences (SSD) or echo cross-correlation peaks, respectively, in both the axial and lateral directions. However, though lesion edge preservation while ensuring the strain continuity is of great importance, none of these techniques are intelligent enough to detect and preserve the lesion edge as well as its natural stiffness variation inside.

In this paper, we propose a lesion edge preserved direct average strain estimation (LEP-DASE) method for elastography. We modify the direct average strain estimation (DASE) technique proposed in [11] by introducing a built-in edge preservation criterion into the average strain estimating cost function. A modified scheme based on [14] is proposed here for lesion edge detection. The performance of this algorithm is evaluated using a FEM phantom, experimental phantom as well as *in vivo* patient data, and compared with other recently reported regularized strain estimation algorithms.

The paper is organized as follows. Section 2 describes the basic DASE and proposed LEP-DASE techniques. Section 3 presents the simulation and experimental results to demonstrate the strength of the proposed algorithm. Section 4 presents a discussion on the study and concluding remarks are given in Section 5.

2. Methods

2.1. Brief Review of the Direct Average Strain Estimation

The simplified 1-D model of the backscattered ultrasound RF signals before and after compression are given by [3]:

$$r_1(t) = s_1(t) + v_1(t) = s(t) * p(t) + v_1(t), \tag{1}$$

$$r_2(t) = s_2(t) + v_2(t) = s\left(\frac{t}{a} - t_0\right) * p(t) + v_2(t), \tag{2}$$

where $s(t)$ denotes the 1-D scattering function of the elastic target, $p(t)$ denotes the point-spread-function (PSF), a denotes the compression factor due to axial deformation of the target medium, t_0 denotes the time delay, $v_1(t)$ and $v_2(t)$ denote the uncorrelated random noise profiles, $r_1(t)$ and $r_2(t)$ denote the pre- and post-compression rf echo signals, respectively, and $*$ indicates the convolution operation. The strain s is related to the compression factor $1/a$ as [4], $s = 1 - a$ where $a \leqslant 1$ and $s \ll 1$.

Hussain et al. [11] proposed a method for direct average strain estimation (DASE) using the weighted nearest neighbor method in order to compensate for the signal de-correlation due to non-axial motion of tissue scatterers and thereby to introduce a built-in smoothing feature in the strain estimation algorithm. Calculated strain from a pair of windowed RF segments for a particular tissue point is assumed to be similar to the strains in the neighboring tissues due to their physical proximity. This assumption, however, works well unless there is a sudden change in the tissue stiffness.

Let $F_1(i,j)$ and $F_2(i,j)$ are the pre- and post-compression ultrasound RF echo frames, respectively. Here, i is the axial depth index and j is the RF A-line index. An effective strain at a point $(i_s j_s)$ on the strain map can be estimated from a corresponding pair of 1-D windowed RF segments $r_1^{(i_s j_s)}$ and $r_2^{(i_s j_s)}$ selected from the pre- and post-compression ultrasound image frames as [11]

$$r_1^{(i_s j_s)}(i) = F_1((i_s - 1)L_v + i, j), \quad \text{for} \quad 1 \leqslant i \leqslant L_i \text{ and } j = j_s \tag{3}$$

$$r_2^{(i_s j_s)}(i) = F_2(round((i_s - 1)(1 - s_{avg})L_v) + i, j), \quad \text{for} \quad 1 \leqslant i \leqslant L_i$$
$$\text{and } j = j_s + \left(j_s - \frac{N_c}{2}\right)s_{avg}v \tag{4}$$

where v represents the Poisson's ratio, N_c represents the number of scan lines in the RF frame, L_v is the axial separation between two successive RF windows in samples and L_i represents the length of the 1-D RF window. The assumption that the approximate applied strain s_{avg} is known a priori is a drawback of the DASE method [11]. In this paper, instead of assuming that s_{avg} is a known constant, we adaptively define it from the estimated previous window strain $S_o(i_s - 1, j_s)$ as [6]

$$s_{avg} = \begin{cases} 0; & i_s = 1 \\ S_o(i_s - 1, j_s); & \text{otherwise.} \end{cases} \tag{5}$$

After stretching the post-compression echo segment $r_2^{(i_s j_s)}$ by a factor α ($\leqslant 1$), the normalized cross-correlation (NCC) coefficient $\rho_\alpha(k)$ between $r_1^{(i_s j_s)}$ and $r_\alpha^{(i_s j_s)}$ is estimated as [19],

$$\rho_\alpha^{(i_s j_s)}(k) = \frac{\sum_{i=1}^{L_i} r_1^{(i_s j_s)}(i) \cdot r_\alpha^{(i_s j_s)}(i+k)}{\sqrt{\sum_{i=1}^{L_i}\{r_1^{(i_s j_s)}(i)\}^2 \sum_{i=1}^{L_i}\{r_\alpha^{(i_s j_s)}(i)\}^2}}. \tag{6}$$

The peaks of $\rho_\alpha^{(i_s j_s)}(k)$ are calculated by using the cosine interpolation for different values of α:

$$M_\alpha(i_s, j_s) = \rho_\alpha^{(i_s j_s)}\left(\arg\max_k\{\rho_\alpha^{(i_s j_s)}(k)\}\right), \tag{7}$$

where M_α is a matrix that contains the NCC peaks. For average strain estimation, a cost function is defined as

$$J_\alpha^{(i_s j_s)} = \sum_{i_0 = i_s - L_a}^{i_s + L_a} \sum_{j_0 = j_s - L_l}^{j_s + L_l} w^{(i_s j_s)}(i_0, j_0) M_\alpha(i_0, j_0), \tag{8}$$

where

$$w^{(i_s j_s)}(i_0, j_0) = e^{-|\lambda_a(i_0 - i_s)| - |\lambda_l(j_0 - j_s)|}, \text{ for } i_s - L_a \leqslant i_0 \leqslant i_s + L_a; j_s - L_l \leqslant j_0 \leqslant j_s + L_l \tag{9}$$

Here, λ_a and λ_l are the weighting factors, and L_a and L_l are the nearest neighbor (NN) factors in the axial and lateral directions, respectively. The weight function $w^{(i_s j_s)}$ is defined in such a way so that the RF windows of increasing distance from the interrogated window are least "emphasized". However, there is no constraint incorporated for the lesion edge preservation in the cost function (Eq. (8)). Thus, instead of a sharp change in the strain profile, a slowly decaying nature of the estimated strain is seen at the lesion edge regions.

2.2. Lesion edge preserved direct average strain estimation (LEP-DASE)

In detecting an edge along a line of intensity pixels, we may face two types of pixels: the noise pixel and the edge pixel (Fig. 1). A noise pixel is one which has much higher or lower intensity than the adjacent pixels having similar intensities. The edge pixel is one which is either on an inclining slope or on a declining. From these topology, we can define the following necessary parameters [14]:

$$D_x = \begin{cases} |I_E - I_W| - \delta; & \text{if} \quad |I_E - I_W| > \delta \\ 0; & \text{otherwise,} \end{cases} \tag{10}$$

$$A_X = \frac{1}{2}(I_E + I_W), \tag{11}$$

$$I'_{S,x} = \begin{cases} I_S - \frac{1}{2}D_X; & \text{if} \quad I_S > A_X \\ I_S + \frac{1}{2}D_X; & \text{if} \quad I_S \leqslant A_X, \end{cases} \tag{12}$$

$$P_X = I'_{S,x} - A_X, \tag{13}$$

where I_E and I_W represent the image intensity values at the east and west neighboring pixels, A_X represents the average of the neighbor-