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A two-step optical flow method for strain estimation in elastography: Simulation and phantom study

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ABSTRACT

Optical flow (OF) method has been used in ultrasound elastography to estimate the strain distribution in tissues. However the bias of strain estimation by OF has previously been shown to be close to 20%. The objective in this paper is to improve the performance of OF-based strain estimation, a two-step OF method with a local warping technique is proposed in this paper. The local warping technique effectively decreases the decorrelation of the signals, and hence improves the performance of strain estimation. Simulations on both homogeneous and heterogeneous models with different strains are performed. Experiments on a heterogeneous tissue-mimicking phantom are also carried out. Simulation results of the homogeneous model show that the two-step OF method reduces the bias of strain estimation from 23.77% to 1.65%, and reduces the standard deviation of strain estimation from 2.9×10^{-3} to 0.47×10^{-3}. Simulation results of the heterogeneous model shows that the signals-to-noise ratio (SNR_e) of strain estimation is improved by 2.1 and 5.3 dB in the inclusion and background, respectively, and the contrast-to-noise ratio (CNR_e) is improved by 6.8 dB. Finally, results of phantom experiments show that, by using the proposed method, the SNR_e is increased by 4.0 dB and 8.9 dB in the inclusion and background, respectively, while the CNR_e is increased by 13.1 dB. The proposed two-step OF method is thus demonstrated capable of improving the performance of strain estimation in OF-based elastography.

1. Introduction

Elastography has received a lot of interest in the last two decades due to its capability to investigate noninvasively the mechanical properties of biological tissues [1,2]. The axial strains estimated in elastography, are interpreted as relative stiffness of tissues [3]. The axial strains are usually obtained from the spatial gradient of the tissue displacements [4,5]. Speckle tracking using ultrasound RF signals and the cross-correlation algorithm [3,6,7] is commonly used to estimate tissue displacements [8]. In addition to speckle tracking, the optical flow (OF) technique has also been proposed to calculate the displacements and strains simultaneously [18].

OF was first proposed as a motion estimation technique in computer vision [9]. Methods for computing OF were first put forward by Horn and Shunk [10]. OF methods employ the hypothesis that signal intensities remain constant along the motion trajectories, so the motion of an object can be expressed in terms of material derivative or total derivative in the OF constraint equation [9,11]. OF has also been used in elastography to estimate tissue motion [12–15]. Both B-mode data [12,14] and RF data [13,15,16] can be used in the OF-based methods to estimate the sub-sample displacements [10,17]. Behar et al. employed OF to estimate cardiac motion from B-mode images [12]. Mercure et al. implemented an OF method on RF data to estimate vascular strain tensor [18]. Zakaria et al. proposed an iterative OF-based method to estimate the axial strain of rat carotids from B-mode data [14]. OF-based strain estimators have been applied to human myocardia [12], breasts [13] and arteries [14,19].

Tissue motion models including rigid translation [32] and affine transformation [23,27] have been used in OF. The affine transformation takes into account the standard transformations of rotations, translations, dilations, as well shear transformations [23], and therefore is capable of estimating the displacements and strains simultaneously [9,22,24,27], while the rigid translational model typically used in speckle tracking can estimate the displacements only [9]. In speckle tracking, the rigid translational model is employed, and the axial strains are usually obtained from the gradient of axial displacements [7,8].

Mercure et al. has investigated the reliability of OF-based strain estimator using a simulated homogeneous model [18]. Their results showed that the bias of strain estimation by OF were close

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to 20% [18]. Hence, it is essential to reduce the bias, i.e., increase the accuracy of the strain estimation, since the clinicians' diagnoses are directly related to the estimation [20]. In order to improve the performance of OF-based strain estimation, a two-step OF method is proposed in this paper. The local warping technique is employed in this method to improve the coherence between pre- and post-deformed signals. Similar to the aligning and stretching methods used in the correlation-based elastography [23], the two-step OF method utilize the local warping technique reduce both bias and standard deviation of strain estimation, and hence improve the accuracy and precision of strain estimation. With the benefit of less strain noise, the two-step OF method is helpful to improve the quality of axial strain images and lesion detectability in the inhomogeneous tissues.

Comparisons between the two-step OF and conventional OF are performed by using simulations of a homogeneous tissue model with uniform elasticity distribution and a heterogeneous model with a stiffer inclusion embedded in a homogeneous background. The Young's modulus of inclusion (75 kPa) is three times stiffer than the background (25 kPa). Experiments on a tissue-mimicking phantom with a stiffer inclusion are also carried out to assess the performance of the proposed method. The Young's modulus of the inclusion (80 ± 12 kPa) is also about three times stiffer than the background (25 ± 6 kPa). The performance of strain estimation are quantified using the bias and standard deviation of the estimated strain in the homogeneous model [6]. For the simulated heterogeneous model and tissue-mimicking phantom, the quality and lesion detectability of axial strain are evaluated using the elastographic signals-to-noise ratio (SNR_e) and contrast-to-noise ratio (CNR_e) [23].

2. Methods

2.1. Conventional optical flow method

Before strain estimation, the integer-sample displacements are first estimated from speckle tracking using 2-D normalized cross-correlation [7,24]. Then, the subsample displacements and strain tensor are estimated from OF method with the tissue motion model of affine transformation. The differences between rigid translation and affine transformation as tissue motion models are the parameters of strain tensors. Tissue motion model of rigid translation only consists of parameters of displacements (axial and lateral), while the affine model is composed of displacements components and full strain tensor (axial strain, axial shear strain, lateral strain and lateral shear strain).

Affine transformation has been used as the tissue motion model in ultrasound-based strain estimation [16,25,26]. The motion model of affine transformation is described in Fig. 1. Points C and C' are the centers of the region of interest (ROI) before and after deformation, respectively. Point A is an arbitrary point within the ROI, and A' is its corresponding position after deformation. Assuming that the lateral and axial displacements of C are u_C and v_C, respectively. The displacements of point A can be given by

$$\begin{aligned} u(x_A, y_A) &= u_C + \varepsilon_{xx}\Delta x + \varepsilon_{xy}\Delta y \\ v(x_A, y_A) &= v_C + \varepsilon_{yx}\Delta x + \varepsilon_{yy}\Delta y \end{aligned} \quad (1)$$

where x and y are lateral and axial directions of ultrasound field, x_A, y_A, x_C, y_C, are the coordinates of points A and C along the lateral and axial directions, respectively. $\Delta x = x_A - x_C$, $\Delta y = y_A - y_C$ are the lateral and axial distance between point A and C. ε_{xx}, ε_{xy}, ε_{yx} and ε_{yy} stand for lateral (normal) strain, lateral shear strain, axial shear strain and axial (normal) strain of the ROI, respectively. The subsample displacements (u, v) and strain tensors (ε_{xx}, ε_{xy}, ε_{yx} and ε_{yy}) are the six motion parameters needed to be estimated.

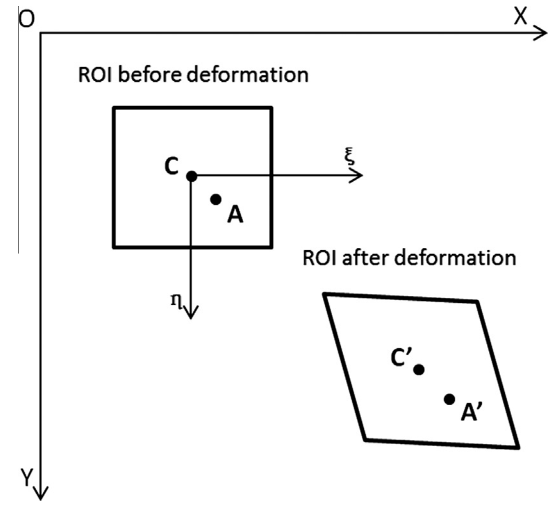

Fig. 1. Demonstration of affine transformation of an ROI before and after deformation.

The motion parameters of affine are calculated by the constraint equation of OF, which is deduced from the assumption of brightness constancy [9–11,28]. Assuming an affine transformation within the small ROI, also called measurement-window [16], the constraint equation of OF is utilized to find the motion parameters. The gradient constraint equation can be expressed as

$$\nabla I \cdot \boldsymbol{u} + I_t = 0 \quad (2)$$

here ∇I denotes the spatial gradient of brightness, I_t denotes the temporal gradient of brightness, and $\boldsymbol{u}$ denotes the motion parameters (displacement components and strain components).

The RF signals are used in the OF constraint equation to estimate the motion parameters in this paper. Denote $f(x, y)$ and $g(x, y)$ as the pre-deformed and post-deformed RF signals of the ROI, respectively. For the RF signals, $\nabla I(x,y) = [f_x(x,y), f_y(x,y)]$ and $I_t(x,y) = g(x,y) - f(x,y)$. Then, the constraint equation (Eq. (2)) with affine transformation (Eq. (1)) becomes [16,27]

$$\begin{aligned} &f_x(x,y)(u + \varepsilon_{xx}\Delta x + \varepsilon_{xy}\Delta y) + f_y(x,y)(v + \varepsilon_{yx}\Delta x + \varepsilon_{yy}\Delta y) \\ &\quad = g(x,y) - f(x,y) \end{aligned} \quad (3)$$

where $f_x(x,y)$ and $f_y(x,y)$ stand for each point's partial derivative in the lateral and axial directions, Δx and Δy stand for each point's lateral and axial distance from the center point of the ROI (i.e., displacements). Using the least-squares method, these parameters could be solved by the following overdetermined linear equation,

$$[\mathbf{f_x}\ \mathbf{f_x}\Delta\mathbf{x}\ \mathbf{f_x}\Delta\mathbf{y}\ \mathbf{f_y}\ \mathbf{f_y}\Delta\mathbf{x}\ \mathbf{f_y}\Delta\mathbf{y}]\left[u\ \varepsilon_{xx}\ \varepsilon_{xy}\ v\varepsilon_{yx}\ \varepsilon_{yy}\right]^T = -[\mathbf{f} - \mathbf{g}] \quad (4)$$

where $\mathbf{f_x}$ and $\mathbf{f_y}$ denote each point's lateral and axial partial derivative, respectively, and are given by,

$$\mathbf{f_x} = [f_x(x_1, y_1), f_x(x_2, y_2), \cdots, f_x(x_N, y_N)]^T \quad (5)$$

$$\mathbf{f_y} = [f_y(x_1, y_1), f_y(x_2, y_2), \cdots, f_y(x_N, y_N)]^T \quad (6)$$

where N is the total number of sampling points within the ROI. So the subsampling displacements (u, v) and strain tensors (ε_{xx}, ε_{xy}, ε_{yx}, and ε_{yy}) of each sampling point can be obtained by solving Eq. (4).

2.2. Two-step optical flow method

Using the conventional OF method, affine parameters of subsample displacements and strain tensors are estimated. However,