GLOBAL TIME DELAY 2D ESTIMATION IN ULTRASOUND ELASTOGRAPHY.

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Background: Correlation methods are commonly used for Time-Delay Estimation (TDE) of tissue displacement. Large correlation windows utilize more information and reduce the estimation variance, but result in significant signal decorrelation and decrease the spatial resolution. Furthermore, most correlation techniques only estimate axial strain because of the poor resolution of ultrasound data in the lateral direction. An attractive alternative approach to correlation-based methods is minimization of a regularized cost function. These methods exploit the prior information that tissue deformation is smooth, and therefore are robust to signal decorrelation [1]. A disadvantage of these methods is their computational complexity, and as such, they are not suitable for real-time implementation. Previous work [2] proposed a real-time method for optimization of the cost function, but only exploited individual RF-lines at during each optimization, which results in artifacts in the form of vertical streaks (Fig. 1).

Aims: This paper presents a novel technique for time-delay estimation of all RF-lines simultaneously instead of utilizing individual RF-lines, thereby exploiting all the information in the entire image. In other words, we optimize for the displacement of all samples of all RF-lines simultaneously, which requires optimizing a cost function with close to 1 million variables.

Methods: The main idea is to incorporate similarity of RF data intensity, as well as prior information of displacement continuity in a cost function. The cost function optimization entails solving a sparse linear system which is computationally efficient. Let $I_1(i,j)$ and $I_2(i,j)$ be two ultrasound RF frames acquired before and after some tissue deformation, and i and j respectively be samples in the axial and lateral directions. The global cost function with the summation on all image pixels is defined as $C = min \sum\{ [I_1(i,j) - I_2(I + a_{i,j} + \Delta a_{i,j}\ , j + l_{i,j} + \Delta l_{i,j})]^2 + \alpha_1(a_{i,j} + \Delta a_{i,j} - a_{i-1,j} - \Delta a_{i-1,j})^2 + \beta_1(l_{i,j} + \Delta l_{i,j} - l_{i-1,j} - \Delta l_{i-1,j})^2 + \alpha_2(a_{i,j} + \Delta a_{i,j} - a_{i,j-1} - \Delta a_{i,j-1})^2 + \beta_2(l_{i,j}+\Delta l_{i,j}-l_{i,j-1}-\Delta l_{i,j-1})^2 \}$ where α and β are regularization terms for axial and lateral displacements respectively. I_1 and I_2 are the corresponding intensity of each pixel in first and second RF frame. Assume an initial estimate of the 2D displacement field is available from Dynamic Programming (DP) [3]. By minimizing the cost function using DP initial guess, the sub-sample axial and lateral displacements ($\Delta a_{i,j}$, $\Delta l_{i,j}$) for the total image are calculated. The integer initial displacements ($a_{i,j}$, $l_{i,j}$) provided through the previous step are added to the subsample displacements. This presents us the final lateral and axial displacements i.e. ($a_{i,j} + \Delta a_{i,j}$, $l_{i,j} + \Delta l_{i,j}$). The spatial gradient of the displacement field is used to acquire the strain image.

Results: We show that the proposed method substantially outperforms the two previous methods of DPAM [2] and normalized cross correlation (NCC) [1] methods using simulation data, phantom experiments and *in-vivo* patient data (Figs. 1, 2 and 3).

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References:

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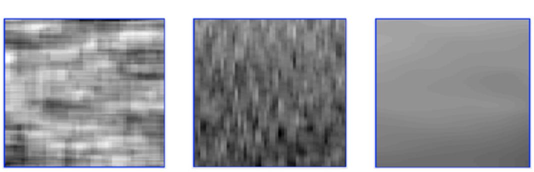

Fig. 1 Left to right: NCC strain, DPAM strain, GTDE strain

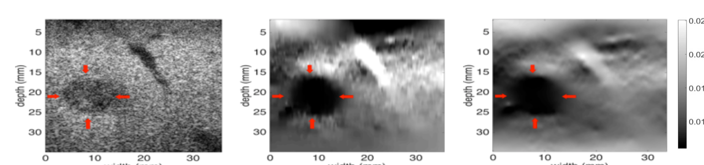

Fig. 2 In-vivo data: BMODE image, DPAM strain, GTDE strain.

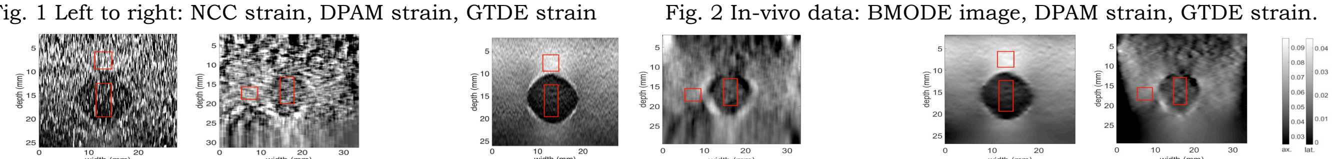

Fig. 3 Axial & Lateral strains of phantom data. Left to right: CC (Ax.), CC (Lat.), DPAM (Ax.), DPAM (Lat.), GTDE (Ax.), GTDE (Lat.)