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A COMPARISON OF MODEL BASED AND DIRECT OPTIMIZATION BASED FILTERING ALGORITHMS FOR SHEARWAVE VELOCITY RECONSTRUCTION FOR ELECTRODE VIBRATION ELASTOGRAPHY

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Abstract

Tissue stiffness estimation plays an important role in cancer detection and treatment. The presence of stiffer regions in healthy tissue can be used as an indicator for the possibility of pathological changes. Electrode vibration elastography involves tracking of a mechanical shear wave in tissue using radio-frequency ultrasound echoes. Based on appropriate assumptions on tissue elasticity, this approach provides a direct way of measuring tissue stiffness from shear wave velocity, and enabling visualization in the form of tissue stiffness maps. In this study, two algorithms for shear wave velocity reconstruction in an electrode vibration setup are presented. The first method models the wave arrival time data using a hidden Markov model whose hidden states are local wave velocities that are estimated using a particle filter implementation. This is compared to a direct optimization-based function fitting approach that uses sequential quadratic programming to estimate the unknown velocities and locations of interfaces. The mean shear wave velocities obtained using the two algorithms are within 10% of each other. Moreover, the Young's modulus estimates obtained from an incompressibility assumption are within 15 kPa of those obtained from the true stiffness data obtained from mechanical testing. Based on visual inspection of the two filtering algorithms, the particle filtering method produces smoother velocity maps.

Index Terms

Electrode vibration elastography; ultrasound; shear wave velocity; particle filter; least-squares fit

1. INTRODUCTION

Information about tissue stiffness variations is extremely valuable for early detection and treatment of cancer [1]. Most cancer diagnosis procedures involve use of some form of diagnostic tissue imaging method. A basic ultrasound scan creates a brightness image (called B-mode image) of the imaging plane allowing visual inspection and delineation of regions based on echographic contrast. However, locating tumors in a tissue background can be quite challenging because echographic contrast may not be easily noticeable on B-mode scans. On the other hand, malignant tissue can be up to an order of magnitude stiffer than healthy tissue [2]. The advantage in using tissue stiffness maps is twofold: stiffness images can help clinicians better delineate malignant regions from healthy tissue, and quantitative

stiffness estimates can provide more accurate information for timing and planning tumor treatment therapies.

In microwave and radio-frequency ablation procedures, an ablation electrode or antenna induces localized heating in the tumor region in order to destroy malignant tissue. This is accompanied by a change in stiffness after ablation. Stiffness monitoring can provide real-time feedback about the size of the ablated region and hence reduce the possibility of partial ablations [3].

Tissue stiffness measurements can be made by inducing mechanical displacement in the regions of interest (ROI) using an external excitation source and then tracking the displacements using ultrasound radio-frequency (RF) data. More specifically, in shear wave elastography, a transverse mechanical wave is induced with the help of an external mechanical excitation. Acoustic radiation force can also be used to provide high intensity localized pushing pulses [4]. By gradually moving the location of the focus of these pulses to greater depths, a line source for shear waves can be simulated [5]. Other forms of mechanical excitation include the use of external pushing rods [6] and manual palpation. In electrode vibration elastography, the ablation needle is itself used as a means for generating shear waves [7].

Two algorithms for reconstruction of tissue stiffness using RF ultrasound echo data are presented in this paper. They are evaluated using ten independent datasets obtained from a tissue-mimicking phantom. Young's modulus estimates are obtained from the shear wave velocity (SWV) estimates by assuming that the phantom material is isotropic, incompressible and elastic. These idealizing assumptions lead to the relation $E = 3\rho c^2$ where E is the Young's modulus, ρ is the density and c is the shear wave velocity.

2. EXPERIMENTAL SETUP

2.1. Tissue mimicking phantom

A specially constructed oil-in-gelatin tissue mimicking (TM) phantom [8] is used to obtain RF ultrasound data for experimental evaluation of the two proposed algorithms. The phantom consists of three regions with different stiffnesses — a stiff ellipsoidal inclusion embedded in a soft background, and an irregular region with an intermediate stiffness protruding on one side of the ellipsoid. A stainless steel needle is firmly bound to the inclusion in order to mimic an ablation needle. The three regions are visible in B-mode due to different echogenicities of the phantom materials used and provides a convenient way to visually gauge the boundary delineation quality of SWV reconstructions. The three materials used in constructing the phantom are tested using an ELF mechanical testing system (Bose Corp., Eden Prairie, MN) to obtain estimates of the actual Young's moduli.

2.2. Shear wave generation

Electrode vibration elastography involves application of a mechanical pulse excitation in the tumor and surrounding tissue and tracking this pulse as it travels laterally outward and away from the source. An actuator together with a servo-controller (Physik Instrumente, Germany) forms the pulse generation system for the experimental setup. The actuator is

firmly fixed to the needle in the phantom. A half-sine shear wave pulse with a temporal width of 30 ms and height of 100 μm is used. Wave pulse amplitude can be controlled easily since the needle is directly bonded to the surrounding phantom material.

2.3. Data acquisition

Custom software for data acquisition is used on an Ultrasonix Sonix TOUCH (Ultrasonix Medical Corp., Canada) scanner using their software development kit which gives full control on the acoustic pulse transmission, reception and beam-forming. Conventional focussed transmit ultrasound imaging does not provide sufficiently high frame rate to acquire data for tracking a shear wave. Therefore, the full data set is assembled by vibrating the needle multiple times and recording data in synchronization at five lateral locations using narrow focussed beams. This provides a frame rate of around 2000 Hz [9]. A 128-element linear array transducer operating at 5 MHz center frequency, 4.5 cm imaging depth, 3 cm focal depth and each A-line sampled at 40 MHz is used for RF echo data acquisition.

3. ALGORITHMS

3.1. Wave arrival time estimation

Assuming that the shear wave travels in a purely lateral direction, a wave pulse can be tracked in the medium by recording the time at which the pulse peak reaches different locations laterally away from the line of the vibrating needle. Axial displacement estimation is performed along each beam line by using a parabolic interpolation cross-correlator with 2 mm windows (≈ 6.5 ultrasonic wavelengths) of RF data and 75% overlap. This generates displacement vs. time plots for each location from which the time of peak displacement is extracted. In order to locate the peak reliably, another parabolic interpolation routine is used. The arrival time is plotted at different lateral locations along lines of constant depth in the image to generate wave arrival time plots (ATP). Since the wave travels with constant velocity in a homogeneous medium, the locations of slope change points can be used as indicators of interfaces between two media and the reciprocal of the slope gives the wave velocity. Hence an ideal ATP can be thought of as a piecewise-linear function whose locations of breakpoints and slopes of the constituent segments are to be estimated from data. An example of a noisy ATP is shown in Fig. 1. The main goal of the two filtering algorithms discussed in the following subsections is to estimate the slope of each segment from this noisy data.

3.2. Hidden Markov model

Lack of prior knowledge about the location and number of breakpoints in the piecewise linear function can be encapsulated in the stochasticity of a hidden Markov model. Suppose that the wave arrival time data is available at equally spaced locations along the lateral direction. Let (X_n, S_n) denote the pair of true arrival time and the true local slope of the ATP at a certain lateral location indexed by n . A recursive relationship between the current function value and the previous slope is given by $X_n = X_{n-1} + S_{n-1}$. Moreover, the slopes are treated as random variables that remain unchanged with a probability q and change to a new value chosen randomly and uniformly over some reasonable interval $[a, b]$ with a probability $1 - q$. Hence the density of S_n conditioned on the previous slope value S_{n-1} is

given by $p_{S_n|S_{n-1}}(\cdot|S_{n-1}=s)=q\delta(\cdot-s)+\frac{(1-q)}{b-a}\mathbf{1}_{[a,b]}(\cdot)$, where $\mathbf{1}_{[a,b]}(x) = 1$ if $x \in [a, b]$ and zero otherwise. The observed data is given by $Y_n = X_n + w_n$, where $w_n \stackrel{i.i.d}{\sim} \mathcal{N}(0, \sigma^2)$ is i.i.d. Gaussian noise. The parameters q and σ^2 must be estimated from raw data. In practice, since the number of interfaces is quite low, the value of q is close to 1. These equations together constitute the Markov state transition structure and the observation function. A particle filter can now be used to unravel the hidden states from the ATP data [10, Algorithm 6], [11].

3.3. Piecewise-linear regression

A piecewise-linear function $f: [0, 1] \rightarrow (-\infty, \infty)$ parametrized by the number of segments B , breakpoint locations $\{\lambda_i\}_{i=0}^B$ and the segment slopes $\{m_i\}_{i=1}^B$ can be expressed as:

$$f(x) = \sum_{i=0}^{B-1} \mathbf{1}_{[\lambda_i, \lambda_{i+1})}(x) \left[m_{i+1}(x - \lambda_i) + \sum_{j=1}^i m_j(\lambda_j - \lambda_{j-1}) \right] \quad (1)$$

where $\lambda_0 = 0$ and $\lambda_B = 1$. Without loss of generality, the lateral locations can be normalized to lie in the interval $[0, 1]$ by rescaling the ATP. An example of a piecewise linear function obeying the form of (1) for $B = 3$ segments is shown in Fig. 1.

If B is known, the problem of approximating the M observed data points $\{(x_n, y_n)\}_{n=1}^M$ as a monotonic increasing piecewise linear function can be stated as a multi-variable optimization problem:

$$\text{minimize } \sum_{n=1}^M (y_n - f(x_n))^2$$

subject to $\lambda_0 = 0 < \lambda_1 < \dots < \lambda_{B-1} < 1 = \lambda_B$ and $m_i > 0$ for $1 \leq i \leq B$. This is solved using a standard sequential quadratic programming numerical optimization routine [12].

A reasonable value for the unknown number of segments can be obtained from a model order selection procedure such as Bayesian information criterion or generalized cross-validation. For this study, the Akaike information criterion [13] was used to find the best value of B . Since there are $2B - 1$ parameters (B slopes and $B - 1$ breakpoints), the AIC can be expressed as

$$\text{AIC} = M \log(\text{MSE}/M) + (2B - 1)$$

where MSE is the mean-squared error of the fit. Different values of B ranging from 2 to 5 were used, and the value of B that minimizes AIC is chosen. This method gives a good trade-off between the mean squared error of the fit and the model complexity.

4. RESULTS AND DISCUSSION

A representative SWV map reconstructed using each of the two algorithms along with a B-mode ultrasound image of the phantom is shown in Fig. 2. The two algorithms perform equally well in terms of visual delineation of the outer inclusion boundary. However, the reconstruction obtained using piecewise-linear regression appears blotchy as compared to the particle filtered image. This is to be expected because the particle filter has the freedom to choose slope values smoothly in a specified interval, whereas the piecewise-linear regression algorithm is forced to approximate the fit with a few straight lines with abrupt breakpoints.

ROIs of size $10 \text{ mm} \times 5 \text{ mm}$ are fixed in each of the three regions of the phantom to obtain quantitative estimates of SWV and Young's modulus. The locations of these ROIs are shown overlaid on the B-mode image in Fig. 2(a). The means and standard deviations averaged over the ROIs and averaged over ten independent data sets are shown in Table 1. The mean SWV estimates obtained from the two methods differ by less than 10% in all the three stiffness regions of the phantom. The mean Young's modulus estimates of the background are within 1 kPa of those obtained from the ELF mechanical testing system, and 15 kPa for the inclusion.

Certain limitations arise from the simplified shear wave propagation model. Viscosity and frequency dispersion can cause the wave pulse shape to change. Both SWV maps show low velocity artifacts around the needle inside the ellipsoidal inclusion. This is probably because the wave pulse takes a certain finite time duration to attain its peak velocity after the needle is vibrated. High velocity artifacts are seen above and below the inclusion because of the assumption that the shear wave front travels purely in the lateral direction. Also observe in Table 1 that the variance of the velocity and Young's modulus estimates are quite high in the stiff region of the phantom. This is because the ATP corresponding to the stiffer region has a smaller slope value that is difficult to estimate accurately [14, Eq. (21)].

5. CONCLUSION

Preliminary results from phantom experiments suggest that there may be merits to using model based approaches instead of *ad hoc* function fitting routines for SWV estimation in shear wave elastography. The extent of gain will have to be quantified through further analysis.

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Fig. 1.

A sample arrival time plot as a function of lateral location is shown. The true function has two breakpoints and three segments. The filtering algorithms must process noisy data shown by the dotted curve to obtain a fit that is close to the true ATP.

Fig. 2.

B-mode image of the phantom consisting of inclusion (i), partially ablated region (p) and background (b) is shown in (a). SWV maps reconstructed using a (b) particle filter algorithm and (c) piecewise-linear fitting algorithm are also shown.

Table 1

Comparison of SWV and Young's modulus estimates

ROI	SWV (m/s)			E (kPa)		
	PF	PL	ELF	PF	PL	ELF
Inclusion	3.8 ± 2.2	3.4 ± 1.5	57.2 ± 70	42.2 ± 58	54.4 ± 0.1	
Partially ablated	2.0 ± 0.2	2.0 ± 0.3	11.9 ± 2.6	12.1 ± 4.2	21.6 ± 0.3	
Background	1.3 ± 0.2	1.4 ± 0.4	5 ± 1.9	6.5 ± 6.1	4.8 ± 0.5	

Values of SWV and Young's modulus of different regions in the two phantoms obtained from particle filtering (PF) and piecewise-linear filtering (PL). Stiffness values obtained from mechanical testing (ELF) are also indicated.