Quantitative Viscoelastic Response (QVisR) Domain Adaption with Fine Tuning

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***Abstract*—Quantitative Viscoelastic Response (QVisR) ultrasound uses *in silico* on-axis VisR displacement profiles to estimate the elastic and viscous moduli of an interrogated material. This work fine-tunes QVisR models with scanner data acquired in a CIRS elasticity phantom to adapt the modulus estimation domain from simulation to phantom. Before fine-tuning, QVisR is able to distinguish material property relative to others within the same image, however it fails to estimate the actual moduli of the materials within reasonable bounds. After fine-tuning, QVisR much more closely estimates the CIRS phantom moduli while still showing the correct relative trends within images. These results suggest fine tuning can be used to adapt simulation trained QVisR models to more realistic imaging environments with a small, labeled dataset.**

***Index Terms*—Acoustic Radiation Force (ARF), Viscoelastic Response (VisR), Quantitative Viscoelastic Response (QVisR), Viscoelasticity, Elastography, Machine Learning**

I. Introduction

Viscoelastic Response (VisR) [1] ultrasound uses a double-push acoustic radiation force (ARF) excitation to interrogate the stress response of viscoelastic materials. Conventional VisR fits tracked displacements to a 1D mass spring damper model [2], [3], and the fit parameters can be rearranged to generate local force amplitude normalized measures of elasticity and viscosity. These metrics are limited to qualitative comparisons since the local force amplitude is generally unknown.

Quantitative Viscoelastic Response (QVisR) ultrasound estimates elastic and viscous moduli from VisR displacement profiles using machine learning [4], [5]. Previous QVisR studies have been limited to model training and evaluations on simulated VisR displacements. Differences in simulation and real scanner acquisition environment (i.e., changes in the estimation domain distribution) would lead to generalization error when using QVisR models to estimate material property. Transfer learning is often used to adapt machine learning models from one domain to another. These techniques is particularly useful when there is an abundance of training data from one domain and very limited data from a similar domain to be used for final model testing. Fine-tuning, a type of transfer learning, uses the model weights from a previously trained model and updates them with further training on a different dataset. This study fine-tunes simulation trained QVisR models with data acquired in a CIRS elasticity phantom to evaluate the ability to adapt QVisR models to non-simulation domains.

II. Methods

A. Simulation Trained QVisR Model

A QVisR model was trained following methods from existing QVisR studies [4], [5]. This study uses an extension of the previous study material database which includes viscoelastic inclusions. Details of the database extension and a summary of the simulation QVisR fit methods are documented below.

1) Simulation Method Summary: VisR displacements were simulated in viscoelastic heterogeneous materials using a Field II [6] and finite element method pipeline developed by Palmeri *et al.* [7]. Acoustic radiation force point spread functions were modeled in Field II and then used as the forcing function for LS-DYNA (Ansys Inc., Canonsburg, PA) viscoelastic material finite element meshes. Resulting nodal displacements through time were mapped to random scatterer displacements, which were then ultrasonically imaged using Field II. White Gaussian noise from 30-50dB SNR was added to the RF data before 1-D axial normalized cross correlation (3λ kernel, 50μm search window) displacement tracking [8].

2) Heterogeneous Material Simulations: The VisR beamsequence applied to the heterogeneous material meshes consisted of ARF pushes with F/3.0 focal configuration and 4.21MHz center frequency as well as tracking pulses at 6.15MHz with aperture growth and dynamic receive focusing. The finite element materials were defined using the Kelvin-Maxwell Viscoelastic material model, a Poisson's Ratio of 0.499, and an equivalent elastic perfectly matched layer (PML). The finite element mesh had a 10mm diameter spherical inclusion centered at 25mm axially. Four elasticities (15.56, 22, 28, 36.67 kPa) and four viscosities (0.01, 1.57, 2.6, 3.9 Pa.s) were paired to create sixteen combinations of inclusion viscoelasticities. The material background was fixed to 26.11 kPa and 2.34 Pa.s. VisR sequences were simulated with ARF push focal depths ranging from 15-35 mm in steps of 5 mm.

3) QVisR Model Fit: Simulated displacements were min-max normalized to remove information related to the unknown applied force amplitude. Normalized displacements were paired with the associated measurement axial depth and ARF push focal depths then used as the input to a multi-layer perceptron neural network trained to estimate the elastic and viscous moduli of the simulated materials. The network was 5 layers deep with tanh activation on the hidden layers and a softplus output activation to enforce positive moduli

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estimates. Huber loss, a combined L1 and L2 metric, was minimized with the ADAM optimizer with a 0.004 learning rate and 4096 displacement profile batch size over 150 training epochs. The model was fit using displacements sampled from both homogeneous and heterogeneous simulations with validation displacements sampled from different random scatterer realizations from the training set.

B. CIRS Phantom Imaging

A CIRS cylindrical elasticity phantom was imaged with a VisR beam sequence using a Siemens Antares scanner and VF7-3 transducer (Siemens Healthineers, Ultrasound Division, Issaquah, WA). Imaging configuration was chosen to match simulations. The phantom inclusions were in a transverse view to approximate the simulated spherical inclusions. Acquisitions were taken for three of the inclusion elasticities (6.49, 15.3, and 49.0 kPa), three inclusion cross-sectional diameters (6.49, 10.41, 16.67 mm), and with three ARF push focal depths (25, 30, 35 mm). Displacements acquired were processed in the same manner as simulations to be used with the QVisR model.

C. QVisR Model Fine Tuning

The simulation trained QVisR model was fine tuned with a subset of the CIRS phantom data for 5 epochs. The optimizer learning rate was lowered to 0.0001 and displacements were sparsely sampled between 20-40mm to reduce overfitting. All displacements from the 6.49 mm cross-sectional diameter and 30 mm focal depth were excluded from fine tune training to be used as a validation set.

III. Results and Discussion

Elastic modulus estimates are shown for both the simulation trained and CIRS phantom fine tuned QVisR models on the phantom validation set. Before fine tuning (Fig. 1 2nd row), model estimates show the correct qualitative trend (i.e. inclusion softer/stiffer than background), but background estimates are not consistent preventing any comparisons between different images. After fine tuning (3rd row), background estimates closely match calibrated values with median absolute errors (MAE) of 0.54, 0.48, and 0.26 kPa (Fig. 1 g, h, i, respectively). Inclusion estimates are most accurate near the center of the inclusion and smooth into the background modulus values near boundaries. Despite the edge underestimation, fine-tuned QVisR estimates still have relatively low MAEs (2.42, 2.41, and 4.60 kPa) measured over the entire inclusion geometry.

Viscosity in the CIRS phantom was negligible, both within the inclusion and background, and QVisR MAE was less than 0.1 Pa.s post fine tune. Since there was no variation in the viscosity of the fine-tuning dataset, QVisR is likely overfitting to isoviscous phantom material which would bias estimates using any viscous materials. Extension to viscous phantoms is a topic of ongoing research.

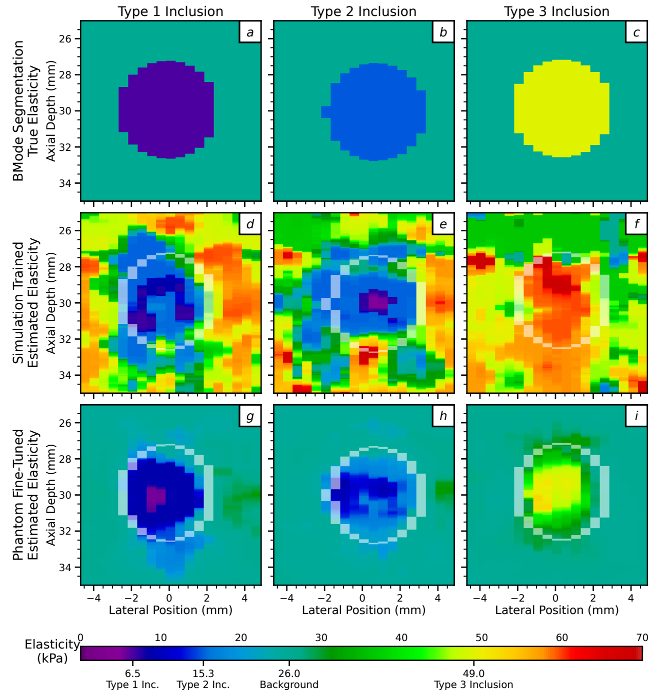

Fig. 1. CIRS cylindrical elastic phantom modulus estimates for simulation trained (middle row) and phantom fine-tuned (bottom row) QVisR models. Top row shows calibrated elastic modulus values with geometry segmented from Bmode. Cylindrical inclusion cross-section boundary overlaid on estimate images as a faint white mask. Inclusion elastic modulus varies by column as indicated by the bottom x-axis of the colorbar. Background elastic modulus for each inclusion type was fixed at 26 kPa. Estimates are shown for 30mm focal depth. Viscous estimates excluded from figure since the ground truth value is 0 Pa.s and phantom fine-tuned model estimates are nearly uniformly 0 Pa.s.

IV. Conclusion

This study shows the validity of fine-tuning to adapt the estimation domain of QVisR models from viscoelastic simulations to elastic phantoms. Future work will focus on incorporating prior information from estimation domain geometry, application of physics informed models, and domain adaption to clinical datasets. This work is part of an ongoing study with further statistical performance analysis and model extensions.

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