Digital Image Correlation-inspired Unsupervised Quasi-Static Ultrasound Elastography on B-Mode Images

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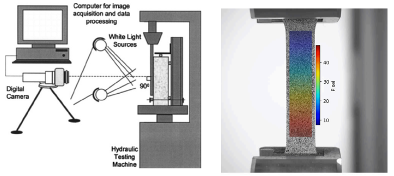
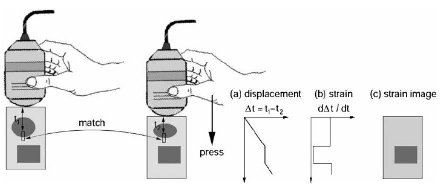
Background

Digital Image Correlation is a non-contact, optical method used to measure full-field displacements and strains on the surface of objects.



In Ultrasound Strain Elastography (USE), quasi-static compression is applied to tissue, and ultrasound RF or B-mode data is used to track tissue displacement, which is then differentiated to compute strain.



Motivation

Applications & benefits of USE:

- Diagnostic aid for cancer, liver fibrosis, etc.
- Extensive use for physiological health monitoring
- Low-cost, non-invasive and real-time

Extensive research conducted on RF Data based Displacement Tracking for USE, but RF Data is not readily available in clinics.

In contrast, B-mode data is:

- Universally available & aligns with established clinical workflows and guidelines
- Simplifies data handling and algorithm implementation

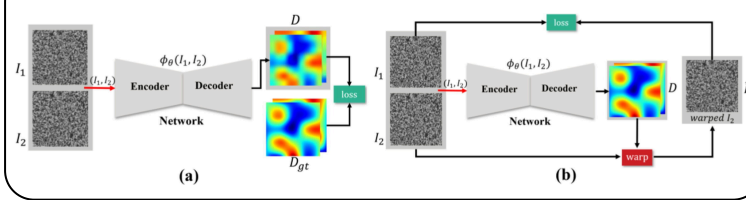
Challenge: In general, it is observed that RF Data based Displacement Tracking for USE outperforms B-mode data dependent methods

Objectives

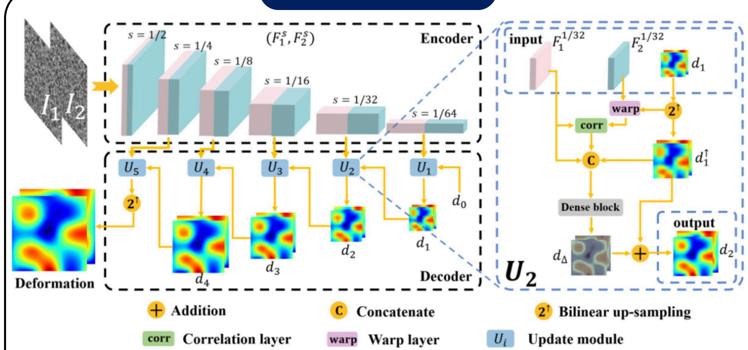
To evaluate the feasibility of Quasi-Static USE for detecting inclusions/lesions using B-mode data only

To provide a ground-truth independent methodology for computing strain maps applicable to *in-vivo* scenarios

Methodology



Model Architecture



Losses:

Patch-ZNSSD Loss: $\mathcal{L}_{\text{ZNSSD}} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{P_i - \mu_{P_i}}{\sigma_{P_i} + \epsilon} - \frac{Q_i - \mu_{Q_i}}{\sigma_{Q_i} + \epsilon}\right)^2$

Smoothness Loss: $\mathcal{L}_{\text{smooth}} = \frac{1}{HW}\sum_{x=1}^{W}\sum_{y=1}^{H}\left(|\nabla_x \mathbf{f}(x,y)|e^{-|\nabla_x I(x,y)|} + |\nabla_y \mathbf{f}(x,y)|e^{-|\nabla_y I(x,y)|}\right)$

Census Loss: $\mathcal{L}_{\text{census}} = \frac{1}{NK}\sum_{i=1}^{N}\sum_{j=1}^{K}|\text{sign}(p_{ij} - p_i^c) - \text{sign}(q_{ij} - q_i^c)|$

Evaluation Setup

Datasets:

- Simulated Datasets (data was post-processed to convert into B-mode images)
  - Alpinion - RF data of simulated phantoms available at [4]
  - ABAQUS - RF data of simulated phantoms available at [3]
- *in-vivo* Dataset
  - B-mode data of patients available at [5]

Benchmarking Methods:

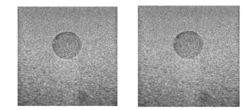
- GLUE: GLobal Ultrasound Elastography - RF Data based classical algorithm [2]

Metrics

$$\text{NRMSE}(\%) = \left(\frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}}{\bar{x}}\right) \times 100 \qquad \text{SNRe} = \frac{\mu_s}{\sigma_s}$$

Results

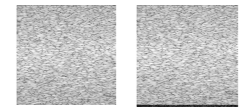
Alpinion



Pre-compression Post-compression

	Ours	GLUE	Ground Truth
SNRe	2.08	2.86	1.74
NRMSE	1.74	1.62	-

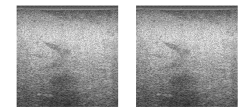
ABAQUS



Pre-compression Post-compression

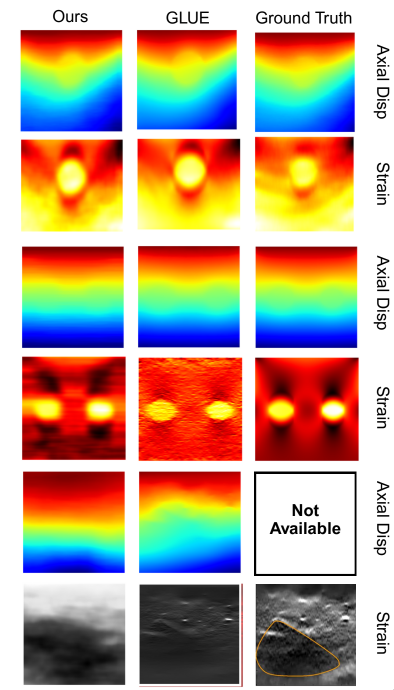
	Ours	GLUE	Ground Truth
SNRe	2.6	6.52	2.47
NRMSE	2.85	2.43	-

in-vivo (zero-shot)



Pre-compression Post-compression

	Ours	GLUE
SNRe	2.17	4.23



Discussion

Summary:

- Results show that our methodology detects inclusions accurately and achieves performance comparable to the "gold standard" GLUE on RF data, highlighting the practical potential of B-mode-based Quasi-static USE.
- While methods on RF data work well for small strains (<2%), reported methodology remains robust up to high strains (4.5%) without the need for ground truth.
- However, our methodology requires large amounts of data and may not generalize well to unseen datasets.

Future Direction:

- Explore real-time implementation for strain mapping and domain generalization.
- Improve performance on *in-vivo* datasets

References

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[2] H. Hashemi, et al., "**Global Time-Delay Estimation in Ultrasound Elastography**", IEEE TUFFC, Oct. 2017,

[3] A. K. Z. Tehrani, et al., "**Bi-Directional Semi-Supervised Training of Convolutional Neural Networks for Ultrasound Elastography Displacement Estimation,**" *arXiv:2201.13340*, Jan. 2022

[4] A. K. Z. Tehrani, et al., "**Displacement Estimation in Ultrasound Elastography Using Pyramidal Convolutional Neural Network**," IEEE Trans. Ultrason., Ferroelectr., Freq. Control, Dec. 2020, doi:10.1109/TUFFC.2020.2973047

[5] Rivaz, H., et al., "**Real-Time Regularized Ultrasound Elastography**", IEEE TMI, April 2011, doi:10.1109/TMI.2010.2091966