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Jason K. Citron
Boston University

Paul E. Barbone
Boston University

Carlos E. Rivas
Boston University

Michael S. Richards
Boston University

Jeffrey C. Bamber
Boston University

See next page for additional authors

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Author(s)
Jason K. Citron, Paul E. Barbone, Carlos E. Rivas, Michael S. Richards, Jeffrey C. Bamber, Nigel L. Bush, and John R. Yarnold

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MEASURING TISSUE DEFORMATION FROM ULTRASOUND IMAGE SEQUENCES

Jason K. Citron[1], Paul E. Barbone[2], Carlos E. Rivas[3], Michael S. Richards[4], Jeffrey C. Bamber[5], Nigel L. Bush[5], John R. Yarnold[5]

Boston University, Boston, MA 02215

Abstract

Elastic Modulus Imaging (EMI) is an emerging and exciting suite of medical imaging techniques. The goal of biomechanical imaging is to map the mechanical properties, for example Young's Modulus, of soft tissues. Physicians find elastography very appealing, in as much as it provides a visual and quantitative representation of what they are trained to detect with their fingertips. Furthermore, it has the potential to see smaller, deeper, and softer inclusions than might be detectable by touch. Medical researchers have identified a myriad of potential applications for elastography, including the diagnosis and treatment of deep vein thrombosis, breast, prostate, and liver cancers, local and diffuse coronary disease, fibrosis, edema and cirrhosis.

In this contribution, we report preliminary results of our novel image registration strategies to sequences of clinically obtained ultrasound images. Our "Least-squares Intensity difference Finite Element" (LIFE) image registration algorithm uses a Gauss-Newton local search strategy to minimize its objective function, and so requires an excellent initialization to converge to the global minimum. The robustness of a novel "Advancing Front" initialization method in handling clinically data was evaluated here. The longer-term motivation is to evaluate the performance of EMI at diagnosing the severity and degree of radiation induced breast fibrosis, an occasional side-effect of radiation treatment of breast cancer.

Image acquisitions were performed as part of a routine ultrasound examination using freehand contact scanning. The ultrasound imaging probe was manually guided to gently palpate the breast through a compliant gel pad of known, tissue-equivalent elastic modulus. The ultrasound scanner (Acuson XP10, 7.5MHz) provided radio frequency (RF) frame sequences corresponding to a compression and shear palpation cycle. Off-line processing of the RF frames by the LIFE algorithm was used to evaluate the deformation of breast tissue and of the calibration pad. Registration accuracy was monitored via a "Registration Quality Indicator (RQI)," as described below.

In about 2/3 of 107 image sequences, the advancing front initialization provided a sufficiently precise initial guess that the LIFE algorithm clearly found the global minimum (as assessed by the RQI). The remaining cases were often characterized by large frame-to-frame motions, low signal-to-noise ratio images, and/or out-of-plane deformations. Most sequences that were acceptable had no poor quality frames, but occasionally large frame-to-frame displacements would result in poor matching of isolated frames; any such frames could be identified via the RQI and removed from the measured deformation data.

The advancing front initialization method is a sufficiently robust initialization strategy to accommodate clinical data. Monitoring registration accuracy via RQI or similar method is critical to identify (un)reliable deformation measurements.

Introduction

Registration techniques as the ones that match two images to calculate the displacement field are important in images processing. they can be used, for example, as an input data to solve the inverse elasticity problem or as intermediate step in other inverse problem. The images used in those problems can be acquired using different modalities, for example computer tomography (CT), magnetic resonance imaging (MRI), ultrasound, etc. In this work, we are studying the deformation of soft tissues using ultrasound imaging in order to determine the mechanical properties of such tissues. For that purpose, ultrasound images of breast tissue were recorded for several patients with breast cancer who had developed stiffer fibrosis tissue. The contrast in elastic modulus (stiffness) from one tissue type to another is enormous which makes very attractive its quantification. In this way, physicians, who are trained to palpate stiffness abnormalities in soft tissue, can have a quantitative representation of what they are trained to detect. The LIFE algorithm was developed to evaluate the displacements of the tissues as the ultrasound probe was guided to palpate the breast. This data was compared to a phantom gel pad placed above the tissue, with a previously determined elastic modulus. By comparing the displacements of the tissue and the phantom gel with known properties, a quantitative estimate of the deformation of the breast was calculated.

Background and Motivation

- Elasticity imaging or elastography is a technique which uses imaging modalities to measure and image relative displacements within tissue volumes. Its main goal is to map the elastic modulus (stiffness) of soft tissues. Tissue stiffness or elastic modulus distribution is believed to be clinically significant and may be correlated to tumor pathology [1].
- Currently, physicians can only qualitatively estimate the stiffness of fibrosis and other tissue with their fingertips. Smaller, deeper, and softer inclusions may not be detectable by touch. The final goal of this study is to recover the spatial variation of the shear modulus.

State of the Art

- One advantage of integrating elasticity imaging into clinical situations is that better assessment of the change of the tissue over time is possible than with current means. By quantitatively measuring the properties of abnormal tissues, better treatment can be provided for patients.
- The motivation behind quantitatively reconstructing the elastic modulus is to uniquely identify specific regions of the breast that are stiffer than normal tissue. Quantitative segmentation of modulus values can increase diagnostic accuracy and repeatability for multiple patient visits or consistency between patients.

Formulation

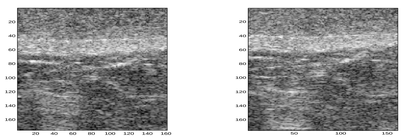
Displacement Field Estimation

- Displacements between images are estimated using the LIFE finite element based image registration algorithm. This algorithm uses a sum-squared image intensity difference objective function (π_1), which is minimized efficiently using a Gauss-Newton method, to produce the tissue displacements. A penalty term for large displacement gradients is added to the functional to help reduce noise in the measurements. The RQI quality indicator was used to remove any data that did not sufficiently determine the global minimum.

$$\begin{aligned}\pi_1(\mathbf{u}(\mathbf{x})) &= Image\,Matching \quad + \quad Smoothness\,Term \\ &= \frac{1}{2}\int_{\Omega}\{|\, I_1(\mathbf{x}) - I_2(\mathbf{x}+\mathbf{u}(\mathbf{x}))\,|^2 \;+\; \alpha\,|\,\nabla\mathbf{u}(\mathbf{x})\,|^2\}d\Omega\end{aligned}$$

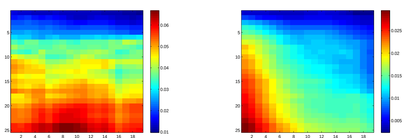
where I_1, I_2 are the images of the tissue before and after deformation, respectively; $\mathbf{u}(x)$ is the displacement field to be calculated and α is the constant that weighs the regularization term included in this formulation.
- For each pair of ultrasound images, we define the matching result. The λ terms are calculated for every pattern of displacement represented in a data sequence. The first two λs, one each representing shear and compressive displacement, are the most significant λ terms, while the others generally represent noise or out-of-plane deformation. So, for a good data, the sum of the λs converges to one with a high rate, while for the poor data the convergence is slow.

Results



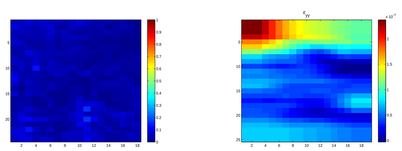
(a) (b)

Figure 1: Ultrasound Images for Real Tissue (a) Before Deformation and (b) After Deformation



(a) (b)

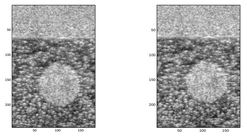
Figure 2: (a) u_x component of the displacement field (b) u_y component of the displacement field



(a) (b)

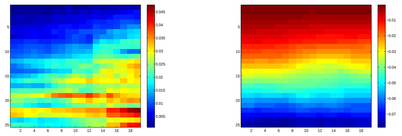
Figure 3: (a) Matching Result for the Images (b) One Component of the Strain Tensor

The displacement field calculated above corresponds to ultrasound images of real tissue. We considered an appropriate constant for the regularization so that the results are smooth and consistent.



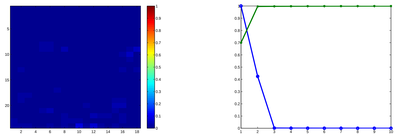
(a) (b)

Figure 4: Ultrasound Images for a Phantom (a) Before Deformation and (b) After Deformation



(a) (b)

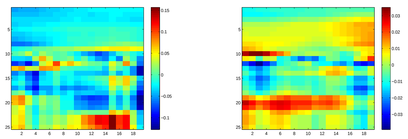
Figure 5: (a) u_x component of the displacement field (b) u_y component of the displacement field



(a) (b)

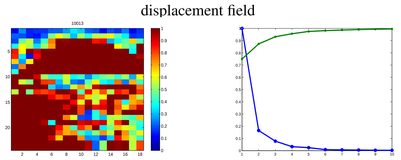
Figure 6: (a) Matching Result for the Images and (b) Blue: Relative Importance of Each Pattern in the Deformation Sequence, Green: Percentage of Deformation 'Energy' Accounted for by First N Modes

We also calculated the displacement field from ultrasound phantom images as seen in Figures 5(a,b). In this case, the regulation term was also considered.



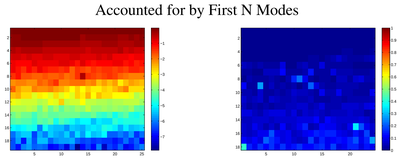
(a) (b)

Figure 7: (a) u_x component of the displacement field (b) u_y component of the displacement field



(a) (b)

Figure 8: (a) Matching Result for the Images and (b) Blue: Relative Importance of Each Pattern in the Deformation Sequence, Green: Percentage of Deformation 'Energy' Accounted for by First N Modes



(a) (b)

Figure 9: (a) Axial Displacement of the Phantom without Regularization and (b) Matching Result for the Phantom without Regularization

Procedure

- In this poster, we show the displacement field for two cases. In the first one, we used ultrasound images that correspond to real tissue, as displayed in Figures 1(a,b). In the second case, we employed ultrasound images from a phantom gel pad as shown in Figures 4(a,b).

Discussion

- Displacements were calculated for the ultrasound images, both from real tissue and from a phantom. From the results, we can see that ultrasound displacement images in the axial direction (u_y) show a high signal to noise ratio, while the other component (u_x) has a lower signal to noise ratio, but still remains physically reasonable. The displacement fields calculated from the phantom images without regularization are still good, as can be seen in its matching image (Figure 9(b)). This implies that the regularization term does not force the LIFE algorithm to find a global minimum. Even without regularization, this method of determining the displacement fields is still valid.
- We show that when the quality of the input images is good, the displacement results are also good. This can be seen in Figures 2, 3(a), 5, and 6(a,b). In addition, when the quality of the images is poor, as in Figures 8(a,b), our code is unable to provide a good results, as seen in Figures 7(a,b). Figures 7(a,b) represent the displacement fields of poor data, which is demonstrated by the discontinuous values and patterns. Figure 8(a) shows poor image matching between these real tissue images, and Figure 8(b) shows that the convergence of the λ terms is slow, which also indicates poor data.
- In two-thirds of the 107 image sequences used in the study, the LIFE algorithm sufficiently determined the global minimum as assessed by the RQI. The RQI was necessary in order to maintain accurate data because the remaining sequences resulted in poor image matching.
- Most acceptable sequences had no poor quality frames, but large frame-to-frame displacements could result in poor matching of isolated frames. The RQI removed such frames in order to maximize the amount of accurate data used to determine the displacements of the tissue.

Future Work

- Future work could involve developing algorithms to determine the quality of 3D images, and also to determine the corresponding 3D displacement fields, which may improve the accuracy of the results, since tissue motion is generally in 3D.
- Developing a practical method for preventing slip between the compliant gel pad and the skin of the patient could also improve results. Slip reduced the accuracy of the displacements because the LIFE algorithm uses one row to estimate the displacement of the following row, and large frame-to-frame motions cannot be approximated as well as small, non-slip situations.

Opportunities for Technology Transfer

- By having a reliable code to calculate the displacement field of tissue, we can determine the elastic modulus distribution. We can then expect this research to have clinical applications in detecting some diseases, such as deep vein thrombosis, breast, prostate, and liver cancers.

Acknowledgments

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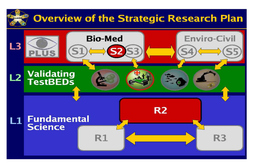

Three-Level Diagram.

References

[1] Jeffrey C. Bamber, Paul E. Barbone, Nigel L. Bush, David O. Cosgrove, Marvin M. Doyley, Frank G. Fueschel, Paul M. Meaney, Naomi R. Miller, Tsuyoshi Shiina, and Francois Tranquart. Progress in freehand elastography of the breast. *IEICE Transactions on Information and Systems*, E85-D(1):514.

1 Department of Aerospace and Mechanical Engineering, Boston University, Boston MA; jcitron@bu.edu

2 Department of Aerospace and Mechanical Engineering, Boston University, Boston MA; barbone@bu.edu

3 Department of Aerospace and Mechanical Engineering, Boston University, Boston MA; cerivas@bu.edu

4 Department of Aerospace and Mechanical Engineering, Boston University, Boston MA; msrich@bu.edu

5 Royal Marsden Hospital and Institute of Cancer Research, Sutton, Surrey, UK