University of Pittsburgh | School of Computing and Information

Proposal Defense

Doctor of Philosophy in Intelligent Systems

"**Physics-Constrained Learning for Tissue Elasticity Estimation from Medical Images**"

by **Matthew Ragoza**

Date: July 9, 2026
Time: 1:00 PM – 2:30 PM
Place: https://pitt.zoom.us/j/93415367444

Committee:

- Dr. Shyam Visweswaran, Professor and Chair, Department of Biomedical Informatics, University of Pittsburgh
- Dr. Kayhan Batmanghelich, Assistant Professor, Department of Electrical and Computer Engineering, Boston University
- Dr. Adriana Kovashka, Associate Professor and Chair, Department of Computer Science, University of Pittsburgh
- Dr. Dana Tudorascu, Associate Professor of Psychiatry and Biostatistics, Department of Psychiatry, University of Pittsburgh
- Dr. Béla Suki, Professor, Department of Biomedical Engineering, Boston University

Abstract:

Tissue elasticity is a clinically significant mechanical property that reflects pathological changes in tissue microstructure, including cancer, fibrosis, and emphysema. Elasticity can be estimated from observed deformation by solving an inverse problem governed by physical equations, but this problem is ill-posed: multiple elasticity fields may produce similar deformation patterns, and solutions are often sensitive to noise, boundary conditions, and modeling assumptions. This dissertation investigates physics-constrained learning methods for estimating spatially varying tissue elasticity from medical images by combining differentiable biomechanical simulation with learned image-based priors. Rather than solving a separate optimization problem for each patient, the proposed framework amortizes elasticity estimation across a training dataset, enabling fast inference without requiring elasticity labels during training.

Preliminary work demonstrates that anatomical information can enhance physics-informed elasticity inversion and that amortized learning can recover heterogeneous elasticity fields from images in a controlled synthetic setting. The proposed research extends this framework to clinical lung imaging, where ground-truth elasticity is unavailable but respiratory deformation can be estimated using image registration. The work investigates three factors that determine whether estimated elasticity maps can be trusted in clinical settings: (1) the complementary information provided by anatomical images and observed deformations, (2) the fidelity of the biomechanical model used to interpret those observations, and (3) the uncertainty that remains when the inverse problem is not fully identifiable under the chosen model. Together, these studies aim to establish a stable, scalable, and credible methodology for estimating tissue elasticity maps from medical images.