Geometric learning for solid mechanics

Steve WaiChing Sun

Associate Professor, Department of Civil Engineering and Engineering Mechanics
Columbia University, New York, USA

Abstract:

This talk presents a framework in which embeddings of high-dimensional manifolds or graphs have been derived as remedies to solve three common solid mechanics problems, i.e., (1) formulation of elastoplasticity models, (2) physics-contained digital twins of geometrical nonlinear shells, (3) inverse designs of materials. In the first example, we conceptualize the yielding surface as a hypersurface in a high-dimensional ambient space spanned by stress and internal variables. This setting enables us to precisely represent the onset of yielding and damages for highly complex materials and metamaterials with coordinate charts collected from RVE simulations. In the second example, our goal is to predict the deformed configurations of Simo-Fox-Rifai shells with an existing database for real-time applications. We introduce a graph isomorphism neural network to generate the response manifold to embed the finite element solutions onto a latent space. Then, we introduce an over-parametrized neural network to extrapolate the responses. To enforce balance principles, we collect an orthogonal basis from the tangential space of the response manifold and solve the POD problems. As such, there is no need for re-training the neural network while deploying the models for time-sensitive applications. Finally, inverse designs of nonlinear materials often involve finding a level set function that searches optimal points in a nonconvex landscape. To fine-tune a material to exhibit a set of prescribed properties with a principled exploration, we adopt a denoising diffusion probabilistic model where a neural network is trained to reverse the Markov diffusion process from the latent space. The denoising process is guided toward generating microstructures with the designated properties by introducing the desired material properties embedded as a context feature vector. To interpret the rationale of the machine learning predictions, we introduce a technique that generates analytical feature space spanned by mapped basis functions. In all these applications, geometric learning provides us with a cohesive tool to systematically connect isolated results to form a broader perspective for understanding the mechanics and design space of materials.

Bio:

Dr. Sun is an associate professor at Columbia University. He obtained his B.S. from UC Davis (2005), M.S. in civil engineering (geomechanics) from Stanford (2007), M.A. (Civil Engineering) from Princeton (2008), and Ph.D. in theoretical and applied mechanics from Northwestern (2011). Sun's research focuses on theoretical, computational, and data-driven mechanics for porous and energetic materials.

Dr. Sun is the recipient of a few awards, including the Walter Huber Civil Engineering Research Prize (2023), the UPS Foundation Visiting Professorship at Stanford University (2022), the IACM John Argyris Award (2020), the EMI Leonardo da Vinci Award (2018), the Zienkiewicz Numerical Methods Engineering Prize (2017), and early career awards from NSF, AFOSR, and ARO.

Monday, November 27th, 2023 4:00 – 5:20 p.m.

1310 Yeh Student Center