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School of Materials Engineering

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Armstrong Hall of Engineering, Room 1103

Unsupervised Learning of Dislocation Motion

Darren Pagan is the staff scientist overseeing the structural materials and mechanics program at the Cornell High Energy Synchrotron Source (CHESS). Darren earned a B.S. degree in mechanical engineering from Columbia University in 2010 and his Ph.D. in mechanical engineering from Cornell University in 2016. His dissertation research focused on developing crystal kinematic and scattering models for quantifying heterogeneous plastic deformation in single crystals during thermo-mechanical loading from *in-situ* X-ray data. As a postdoctoral researcher at Lawrence Livermore National Laboratory, Darren developed new methods for integrating diffraction data with crystal plasticity finite element modeling and used X-ray techniques to characterize granular material deformation *in-situ* under quasi-static and dynamic loading conditions. Darren's current research focuses on developing data analysis methods for quantifying material deformation in metallic alloys and composites, and experimental capabilities for characterizing microstructure evolution during materials processing.

Abstract: High-performance designs that utilize metallic alloys are driving a need to *quantify* deformation *in-situ* at the finest length scales in order to reduce weight, increase operating temperatures, and improve fatigue life. With improvements to data reconstruction algorithms, brighter X-ray sources, and more efficient detectors, these *in-situ* studies of microstructural and micromechanical evolution in 3-D (nm-µm length scales) and at rapid time scales (<ms) are now possible. As numerous projections are often required for inversion of 3-D physics-based scattering models, trade-offs typically must be made between microstructural detail and the time scale probed. Instead, utilization of unsupervised learning, specifically locally linear embedding (LLE), is proposed to analyze *in-situ* diffraction data and find lower-dimensional embeddings that characterize microstructural *transients*, thus by-passing the need for a scattering model chosen *a priori* and enabling material understanding to be recovered with sparser data sets. The approach is applied to diffraction data gathered during uniaxial deformation of additively manufactured Inconel 625. The evolution of the lower-dimensional representation of microstructure is directly connected to the evolution of the defect densities that dictate strength and plastic flow behavior using a well-established material model. The implications of the findings for future constitutive model development and wider applicability to the study of material evolution during processing, particularly additive manufacturing, will be discussed.