LEARNING THE PHYSICS OF FRACTURE PROPAGATION AND FAILURE

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Brittle failure in certain natural and engineered materials is a source of concern for numerous applications, including aircraft wings, ceramics in dental implants etc. Microstructural information (fracture size, orientation, etc.) plays a key role in governing the fracture propagation for these systems but are only known in a statistical sense. Modeling micro-fractures using Finite Element (FEM) or Finite-Discrete Element methods (FDEM) requires massive computational power due to the high spatial and temporal discretization required. Hence most models either ignore or idealize fracture interaction and coalescence at the microscale because we lack a computationally viable framework to do so. We have developed a method to exploit the underlying discrete structure of fractures in brittle material systems by modeling propagating fractures as dynamic graphs. We discover compact graph representations that require significantly fewer degrees of freedom (dof) to capture micro-fracture information and emulate the physics of fracture interaction and coalescence using various Machine Learning (ML) techniques. We generated fracture and failure data using 185 simulations of our high-fidelity FDEM software and used 150 simulations for training and 35 for testing. We compare different ML approaches that include combinations of topological and physical considerations, such as fracture orientations, inter-fracture tip distances, stress concentration factors at fracture tips and influence of the fracture process zone. Quantities of interest include times and paths to failure. Additionally, some methods yield accurate predictions of crack length statistics as they evolve over time. The performance of the different ML approaches with regards to the different metrics gives us insight into developing a hybrid ML-based emulator of our high fidelity model.