CRUNCH Seminars at Brown, Division of Applied Mathematics

Friday - November 12, 2021

How Machine Learning can help in earthquake control and fault mechanics?

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Earthquakes nucleate when large amounts of elastic energy are suddenly released due to abrupt sliding over seismic faults. Besides physical causes, this energy release can be also triggered by injecting large amounts of fluids in the earth's crust. Indeed, recent experience shows that injections can reactivate existing seismogenic faults and induce/trigger important earthquakes [see 1,2]. However, one can see the problem of fluid injections from another perspective [3]. The dependence of fault friction on fluid pressure can be used as an input for stabilization. New results based on the mathematical theory of control [4,5] show that (a) it is indeed possible to stabilize and restrict chaos in this kind of non-linear, unstable frictional systems and (b) assure slow frictional dissipation toward desirable global asymptotic equilibria of lower potential energy. These theoretical results are validated through a series of numerical analyses and experimental tests [4-7] using full and reduced order models of seismic faults. Reinforced learning is also used as an alternative to the rigorous mathematical theory of control for the design of robust controllers for discrete-time control [8]. Our mathematical derivations prove that earthquake control is robust and possible, provided that fault friction is bounded. Friction is a complex phenomenon involving several spatio-temporal scales and complex dynamics. In spite of complexity, the finiteness of energy of any physical process influencing friction as well as existing laboratory and in-situ experiments, support the boundedness of the friction coefficient. However, the quantification of these bounds is challenging as experiments are impossible to perform deep down in the earth. Therefore, we have to rely on numerical simulations and digital twins of seismic faults, which until now are computationally very demanding. To this end, we develop a novel deep learning approach for modeling complex materials, by enforcing the universal laws of thermodynamics [9-12]. The method is accurate, fast and scalable, and will allow, in the near future, to derive reliable quantitative estimations of the bounds of fault friction under the effect of multiphysics couplings and complex grain/particle dynamics. In parallel, it will enable to optimize our earthquake control strategies by performing large scale simulations of real fault systems in a virtual, data- and physics-driven environment, that fits on a laptop.