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MACHINE LEARNING FOR THE PREDICTION OF LOCAL ASTEROID DAMAGES

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ABSTRACT

Risk assessment studies of local asteroid hazards traditionally simulate the physics of meteors with semi-analytical equations tailored to analyze large numbers of scenarios. The engineering models employed encapsulate the mechanisms of asteroid breakup, drag, ablation, energy deposition, thermal radiation, and blast overpressure by solving a set of time-dependent ODEs from a tractable list of physical parameters. However, even with this relatively simplified approach, the computational cost to simulate one asteroid impact scenario is O(0.01 CPU.seconds), thus requiring large distributed systems to solve the hundreds-ofmillions of instances in risk assessment studies. To increase computational efficiency, we propose in this work to replace physics-based approaches by datadriven models for the prediction of local asteroid hazards. We obtain surrogate models that can predict the radius of damaged areas with less than 5% error, and the CPU time required to simulate the 100 million scenarios shrinks from around 10 days to a few seconds.

More specifically, we develop the first machine learning models to predict the main local asteroid hazards: blast overpressure and thermal radiation. We use the stateof-the-art fragment-cloud model (FCM) and the probabilistic asteroid impact risk method (PAIR) developed by NASA's Asteroid Threat Assessment Project to train the machine learning models. The goal is to predict the size of a damaged area for a certain damage severity (e.g., 2 psi blast overpressure, 3rd degree burn, etc.) given a finite set of entry parameters (e.g., velocity, diameter, strength, etc.). We implement several cutting-edge machine learning models including random forests, gradient boosters, and deep neural networks, and validate them against synthetic datasets generated with the FCM and PAIR models. We observe that the data-driven approaches are able to infer the size of the damaged areas with great accuracy for any damage severity, with coefficients of determination (R2) ranging from 0.77 for linear regression to 0.99 for deep neural networks.

Furthermore, we incorporate the machine learning models into a sensitivity analysis to explain how much each entry parameter contributes to increasing the size of the local damages. The sensitivity analysis is based on the Shapley values method and can help the mission design teams in their calibration of the mitigation response by providing information on the combination of entry parameters producing the highest damage levels (e.g., a certain range of incidence angles, high absolute velocities, etc.).

The code and models will be available on a simple github repository with all the instructions to easily train, test, differentiate, run sensitivity tests, and integrate the code on local computers.

Comments:

Impact Effects & Consequences session No preference on timeslot Oral presentation preferred