Study of macro-earthquake generation and fracture coalescence by seismic simulations using the Fiber Bundle Model and Machine Learning techniques.

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ABSTRACT

Earthquakes are the result of rupture processes in the Earth's crust. Computational physics offers alternative ways to study the rupture process in the Earth's crust by generating synthetic seismic data using physical and statistical model. The Fiber Bundle model (FBM), describes the complex rupture processes in heterogeneous materials in a wide range of phenomena. It has shown the ability to generate data that depicts the main characteristics of real seismicity. High-performance computing (HPC) combined with Machine Learning (ML) techniques provide a good ground base to perform and improve the simulations, the data management process and data analysis. In this study we use ML on seismic series to determine the existence of patterns that reveal optimal input parameters that simulate real seismic sequences.

KEYWORDS

Seismic rupture processes, Fiber Bundle model, Machine Learning.

1 INTRODUCTION

Although we have knowledge about the occurrence of certain major earthquakes, our observational span is still too short to be able to draw strong (predictive) conclusions about when, where and how big the next earthquake will be. Earthquakes can be studied from either a physical or a statistical point of view. The statistical approach considers earthquakes as stochastic point processes [1–3]. The Fiber Bundle Model (FBM)[4], is a cellular-automaton model based on the interactions of individual cells, featuring particular transfer load rules and a probability distribution function describing the intrinsic cells properties. Its simplicity offers many advantages and an adaptability to describe a wide range of phenomena.

2 METHODOLOGY

To analyze the synthetic seismic series generated with the FBM we applied supervised learning methods in order to:

1) determine the minimum grid size using machine learning methods such as Random Forest, Flexible Discriminant Analysis, and Support Vector Machines [5].

2) identify the most relevant input parameters of the simulation (i.e. percentage of conserve load, initial organization probability) using statistical analysis and machine learning methods.

Once optimal input parameters are estimated, we validate the model using real seismic sequences and the corresponding spatial distribution of their faults systems. The fracture coalescence is studied using complex networks theory applied to synthetic and real series. In this sense we are analyzing the evolution of the ruptures to quantify where, and under which conditions, two or more fractures are concatenated.

3 SUMMARY

The novelty of this work lies in the study of the Earth rupture processes and fault coalescence by using a general rupture model called Fiber Bundle Model with the incorporation of real and synthetic fault systems. Moreover, ML techniques are used to exploit seismic patterns that allow us to estimate optimal model parameters to reproduce the Earth faults coalescence and the aftershocks generation.

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