Applying Unsupervised Machine Learning to Characterize Experimental Stick-Slip Cycles

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ABSTRACT: Machine learning has recently proved to be an extremely useful tool in earthquake physics. In particular, recent advances at Los Alamos in collaboration with Penn State have shown that by listening to a time series signal recorded from a shear experiment it is possible to predict the time to failure of the next slip event, the magnitude of the event and the instantaneous friction value. Motivated by these recent discoveries we seek to identify previously unknown signals in an acoustical time series signal. We have conducted a suite of shear experiments using a biaxial deformation apparatus in the double-direct shear configuration. Experiments are carried out using simulated fault gouge over a range of experimental boundary conditions. Acoustic data was recorded at 4 MHz from 36 p-polarized piezoelectric transducers. The transducers are embedded in a 10 cm x 10 cm steel block and located adjacent to the fault zone. Using a moving time window through the acoustical time series we have extracted 40 statistical features related to the acoustical data characteristics. We then use these statistics as input features to the mean-shift algorithm. This algorithm identifies areas of clustering within the 40 dimensional feature space. Preliminary results suggest only a small subset of these 40 features are useful in differentiating between clusters throughout the stick-slip cycle. Furthermore, we hypothesize that the differences between clusters is related to the state of stress, amplitude and frequency of acoustic emissions. Based on our preliminary results, we hypothesize a clustering analysis could differentiate between dynamically triggered and non-triggered slip events. This is currently impossible. Future work will involve conducting a clustering analysis on laboratory data sets which have acoustically triggered and non-triggered events. Our intention also is to determine if signals can be identified that previously have been missed.