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Rapid recognition of fracture-generated phase components using machine learning methods

PURDUE UNIVERSITY

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Challenges & Objectives

- **Challenges:** Precursor(s) to the induced seismicity from existing fracture systems - linking mechanical discontinuities, fracture mechanics, pore pressures/stress to the geophysical signatures – is key, yet remains elusive as a result of the heterogeneity and resulting scale dependence
- **Objectives:** An ambitious integration of seismic imaging experiments coupled with micro-CT imaging, modeling of fracture initiation and propagation, and full waveform inversion will allow us to

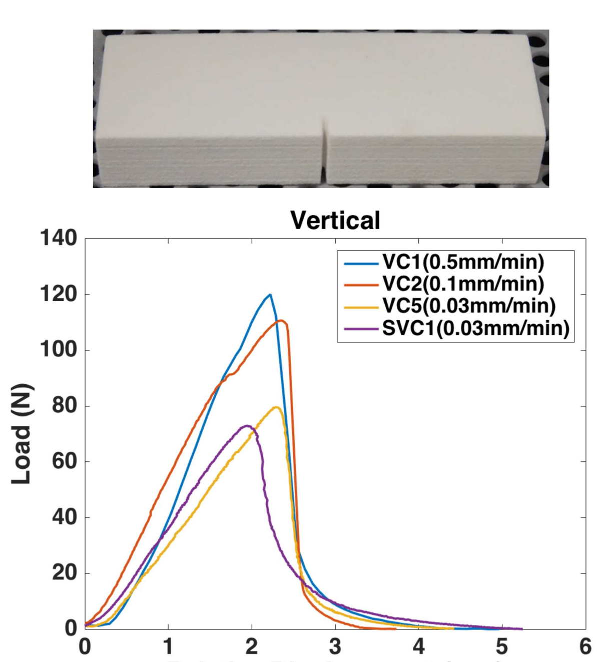
(1) delineate crack initiation, propagation and failure using both active and passive seismic/ultrasonic monitoring techniques

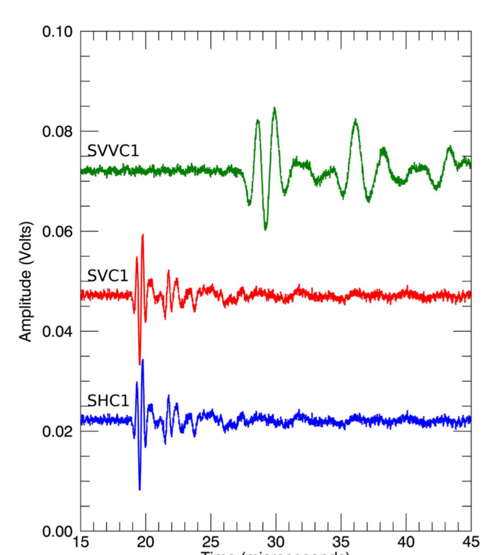
(2) determine the mechanical failure mechanisms that lead to induced seismicity from crack propagation and the best seismic imaging modality & precursors to the slip

(3) develop and implement automatic identification and interpretation of (micro-)seismic wave fields using machine-learning techniques that automate phase selection in spatial-temporal datasets and yields statistical information on the properties of data

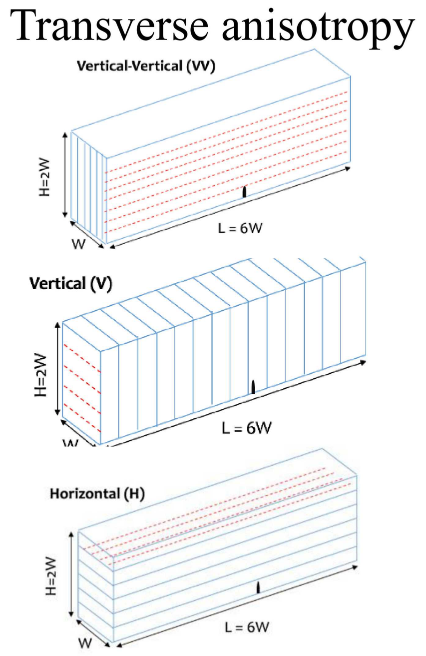
Fracturing Testing and Seismic Signal Acquisition

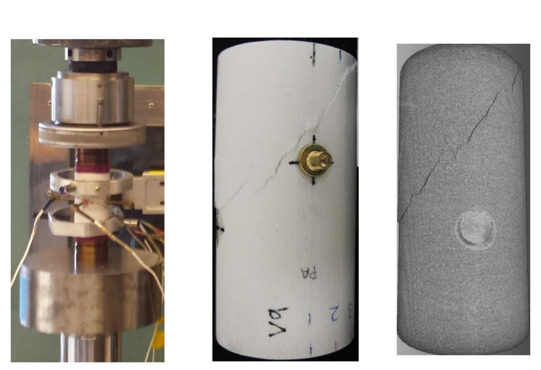
- Testing specimens for three point bending (3PB, top) and unconfined compressive strength tests (UCS, bottom) were created using a powder based 3D printing technique (see **MR33A-06** 14:55 - 15:10 (Jiang et al.) for the details)

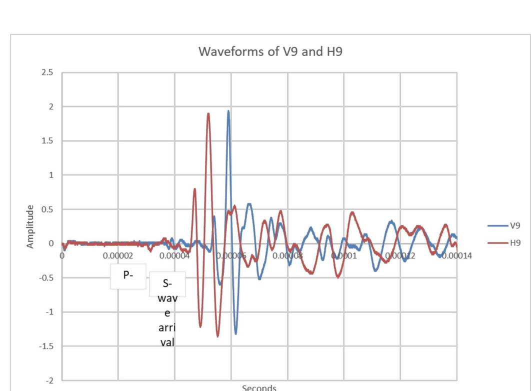


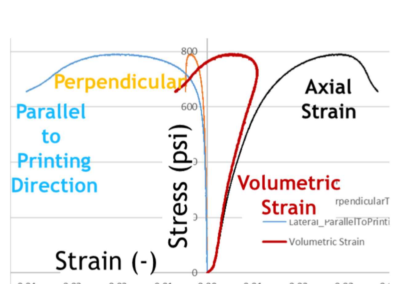


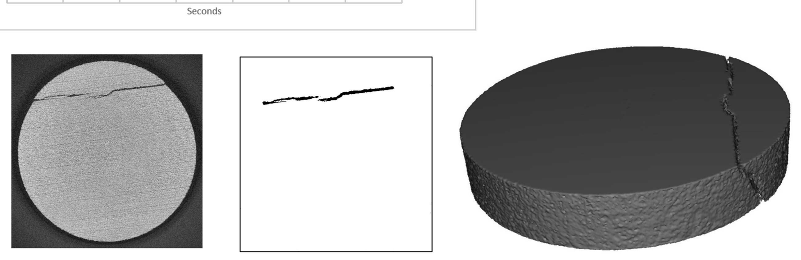
Transverse anisotropy









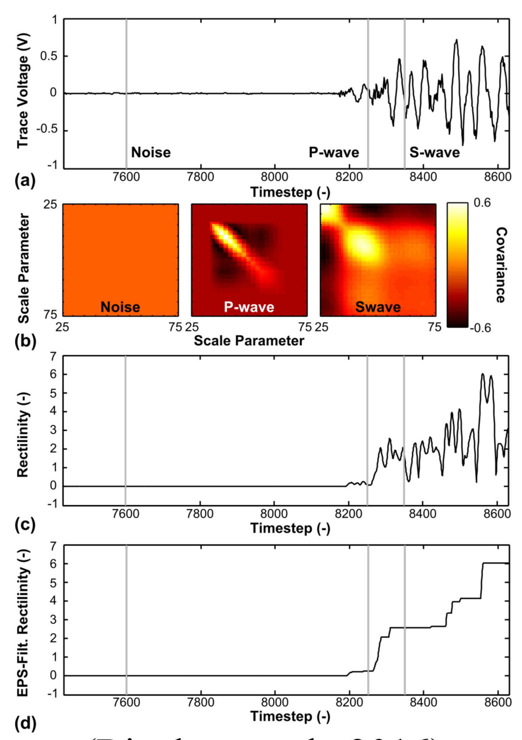


Original microCT image (left), segmented image of crack (WEKA in Fiji), and reconstructed 3D segmented image (right) for UCS tested sample

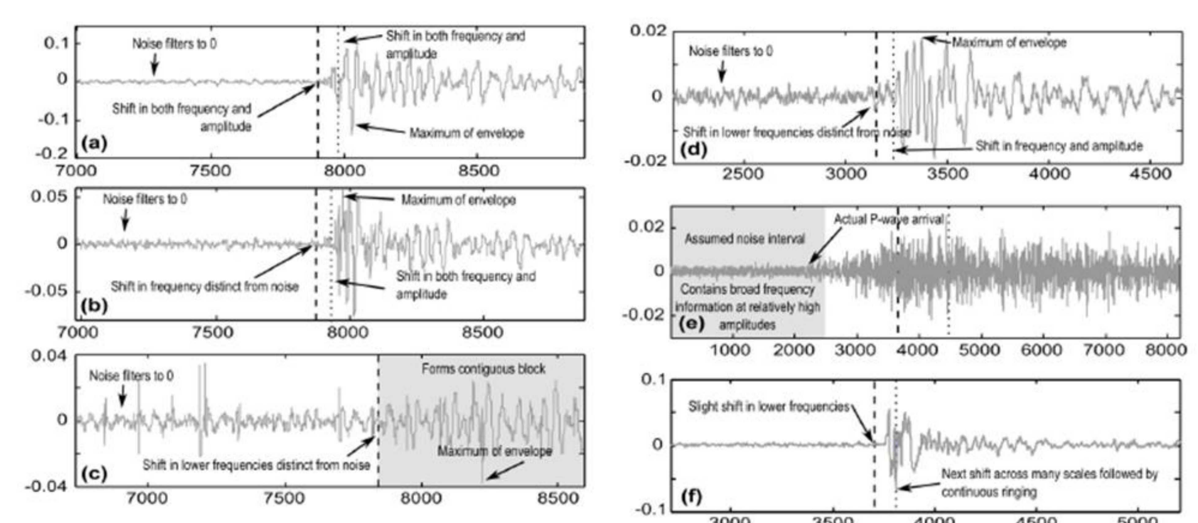
Acoustic Emission Signal Processing

- Wavelet scale covariance analysis of P- and S-waves arrivals **(Rinehart et al., 2016)**

- Combine wavelet-based de-noising with filtered metrics based on the covariance of the continuous wavelet transform (b) of the signal (a)
- An edge-preserving rectilinity function captures the variance and rate of decay of eigenvalues of the covariance matrices (c).
- P- and S-wave arrivals are found sequentially by thresholding (d)



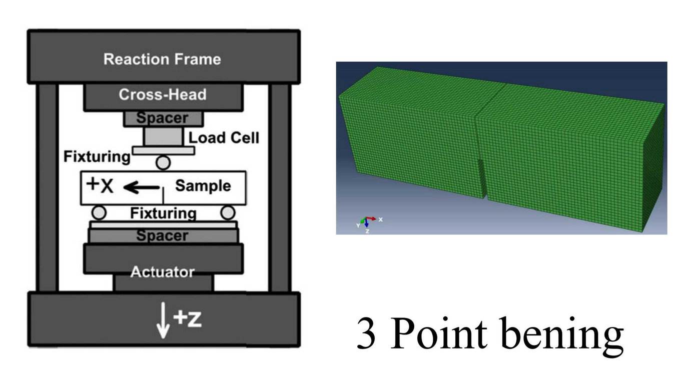
(Rinehart et al., 2016)



Examples of different event traces with P-wave arrival time (dashed) and S-wave arrival times from fracture toughness tests in aluminum (a-c) and Cranfield caprock failure tests (d-f).

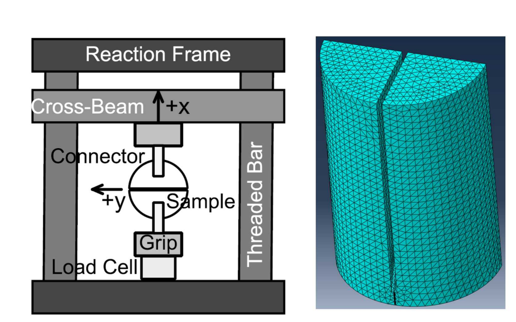
- High success rate in automated picking for P- and S-waves
- Not so good for low-magnitude "rumbling events" and with high electrical noise
- Low amplitude long term events could be discerned by further thresholding in amplitude

Numerical simulations of Crack Propagation and Acoustic Emission



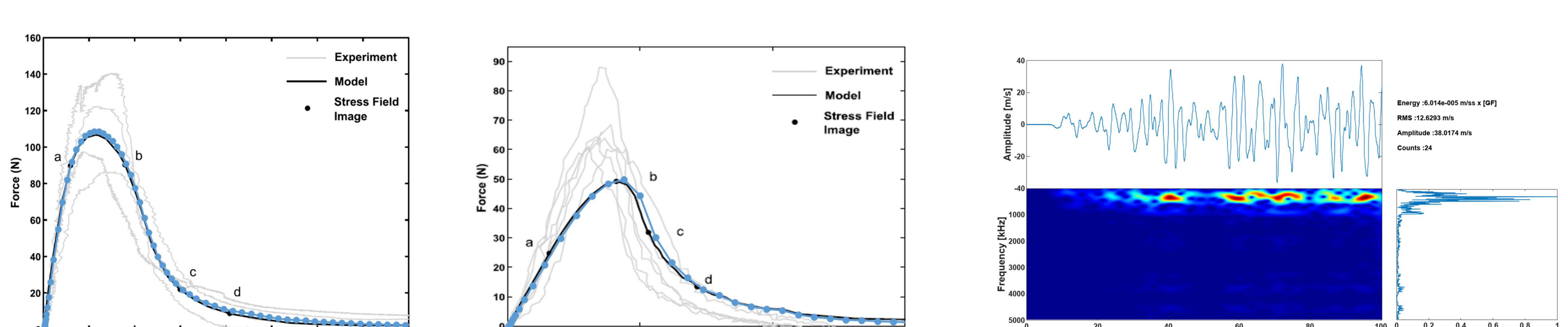
Rinehart et al., 2015

3 Point bening



Short-rod testing with Chevron notch

- Crack propagation with cohesive element model & XFEM (ABAQUS)
- Acoustic emission with XFEM (ABAQUS)
- FFT/STFT to create spectrogram (Cuadra, 2015)



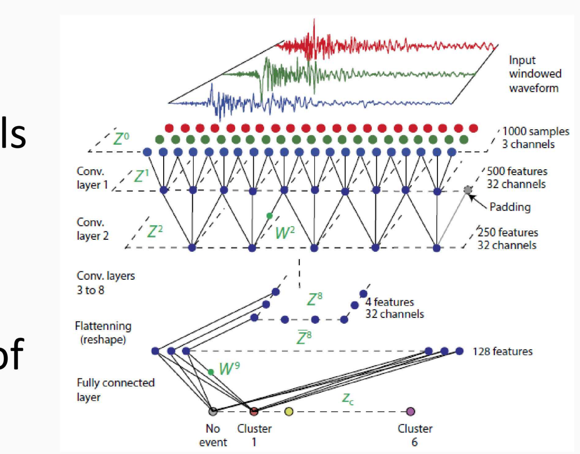
Acoustic emission during tensile cracking (left: 3PB; middle: short rod test) and associated spectrogram during 3PB (ABAQUS simulation result)

Proposed ML approaches

- Architecture and parameters of the DNN

- Deep convolution neural networks was adopted to develop the GANs in this study.
- Fully convolutional nature of GANs allows the stable training and the generation of large samples that contains the similar properties with computational efficiency (Radford et al., 2016).

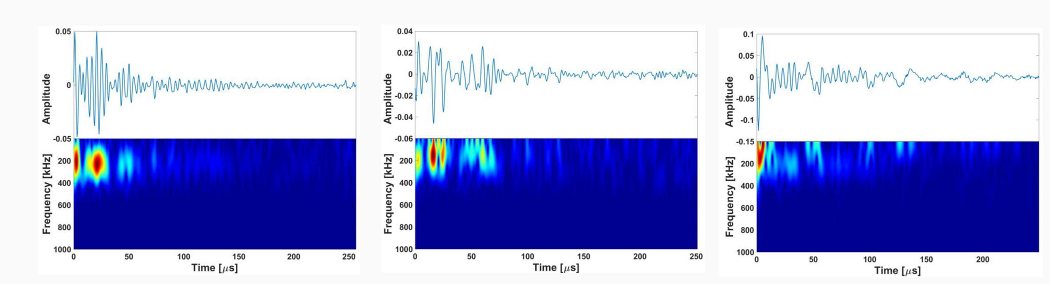
Open source ConvNetQuake (Perol et al., 2018)
Processed data from ISGS will be used to train models
Efficiency and interpretability will be compared with FAST and template matching
Trained model will be used to validate again the remaining dataset to develop real-time recognition of events and locations

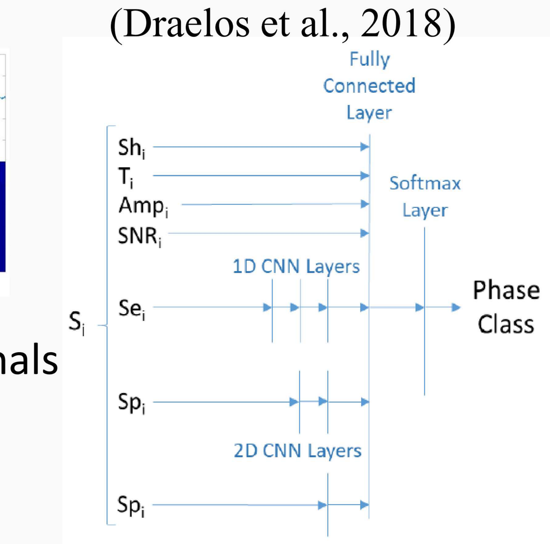


ConvNetQuake CNN Architecture
Perol et al. (2018, SciAdv 2018)

- Seismic Phase Identification with a Merged Deep Neural Network

(Draelos et al., 2018)





(Top) Examples of amplitude and frequency of AE signals obtained during unconfined compressive strength testing of 3D printed specimen.

(Rigth) Example merged DNN for Phase ID. S_i (input signal), Sh_i (horizontal slowness), T_i (time since the previous detection), Amp_i (amplitude of the detection), SNR_i (signal to noise ratio), Se_i (seismogram),and Sp_i (spectrogram) of the waveform.

Goal: Combination of well controlled lab and simulated data with field data will enhance the data analytics using advanced machine learning algorithms to detect arrival times of body waves, converted modes and guided-modes, the relative amplitudes (energy partitioning) among these different wave components, and the frequency/dispersive properties of these waves

References

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