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Integrated machine learning models of event detection and source location identification for fault imaging using raw continuous IBDP microseismic data

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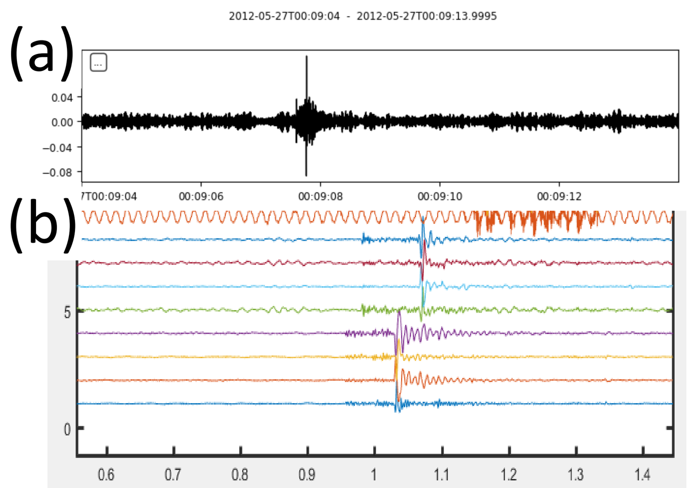
SMART

Science-informed Machine Learning to Accelerate Real Time (SMART) Decisions in Subsurface Applications

Motivation: For estimating microseismic (MS) source locations we develop a framework using multiple deep learning (DL) approaches for continuous waveform data observed at the Illinois Decatur Basin Project (IBDP) site [1] (Fig. 1).

IBDP Site: Continuous waveform data over a short time period (2/27/2012-03/12/2012) are analyzed with a total of 612 located MS events in the catalog.

- Data pre-processing of raw continuous microseismic data & event detection
- Data augmentation using WGAN (Wasserstein Generative Adversarial Network)
- PhaseNet used to downselect generated event data with high quality
- CNN model with multi-modal input for source location estimation of events



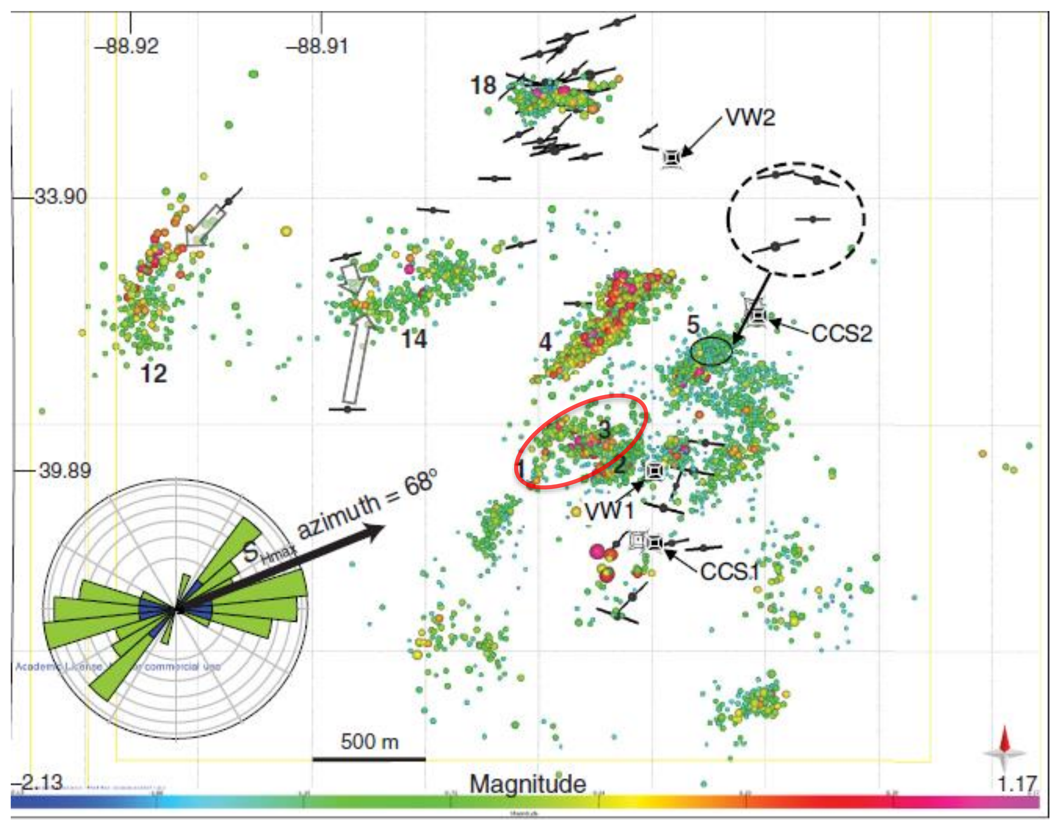


Figure 1. (a) 10s raw continuous waveform data, (b) examples of multiple channel waveform, (c) IBDP site events and cluster #2 overview. [2]

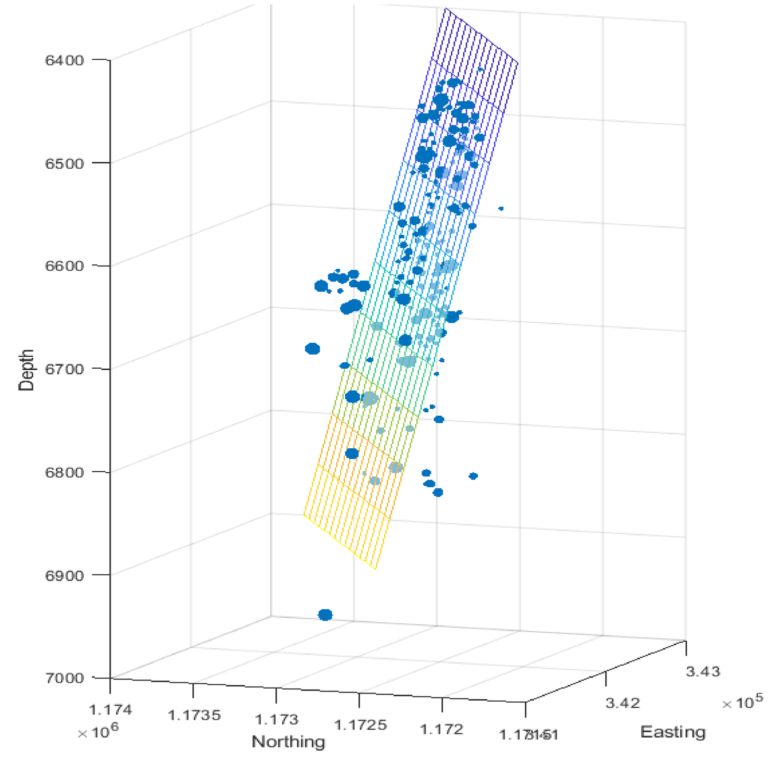


Figure 7. Fault plane estimation.

Event Detection (Figure 2)

- Develop a DL model (with spectrogram input) for fast and accurate MS event detection despite data limitations
- Obtain accurate detection over a variety of MS event characteristics

Phase-pick (Figure 3)

- Train a PhaseNet [4] model with transfer learning to optimize the model for MS events
- Obtain high precision MS waveform phase arrival time information.

Source Location (Figure 5-7)

- Develop a DL model with multiple modality feature extraction capabilities for high fidelity MS event source location identification.
- Implement trained model on field data to identify discrete fractures.

Data Augmentation for Source Location Estimation(Figure 4)

- Train a multi-channel WGAN-GP [3] model to emulate field MS waveform characteristics for a given event source locations.
- Use trained models to generate new waveform data for a range of locations around fault regions.

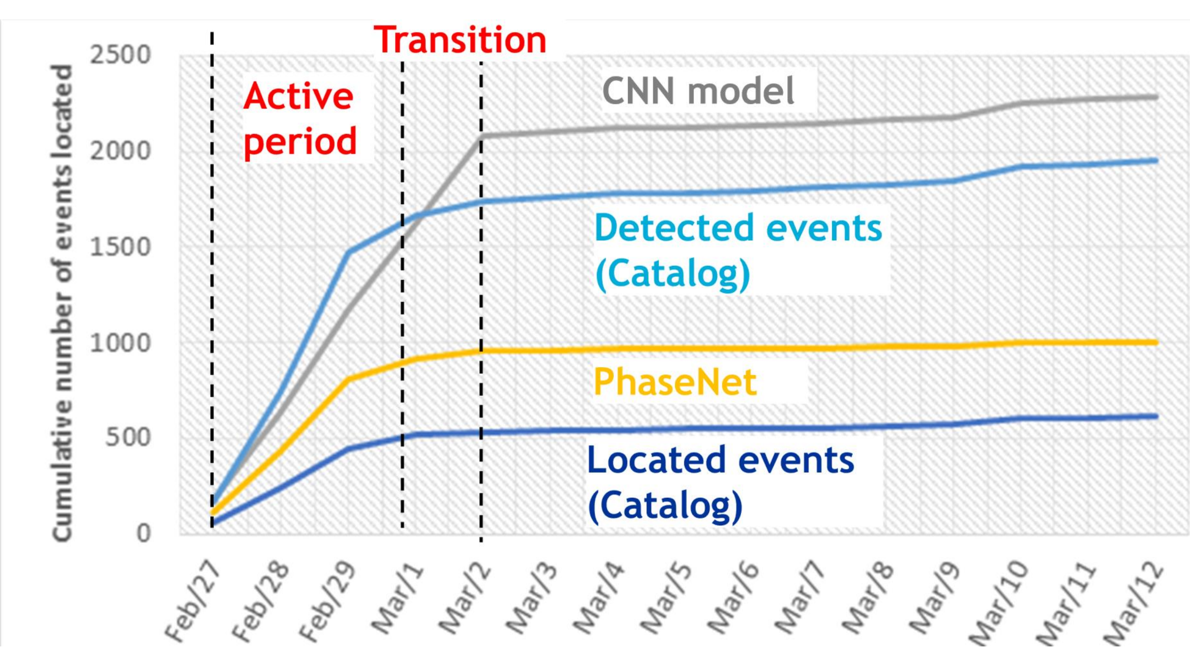


Figure 2. Cumulative detection of MS events using traditional and DL algorithms. Our DL Models achieve better precision than traditional methods.

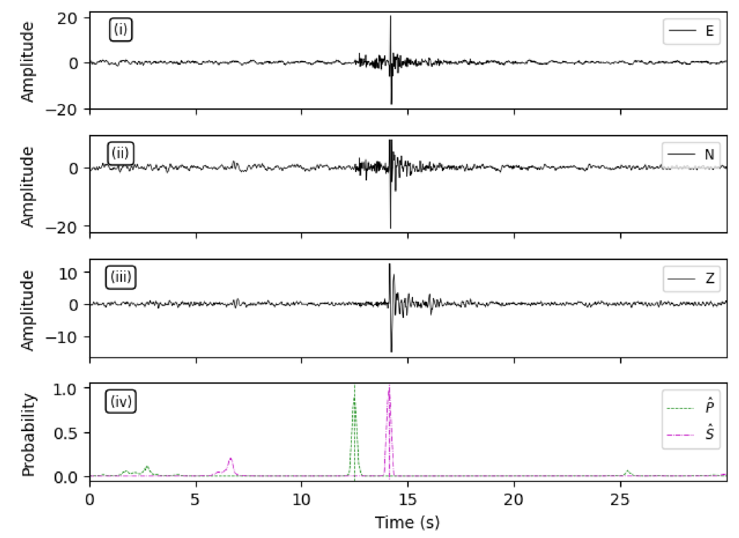


Figure 3. Example of PhaseNet phase (p & s) picking.

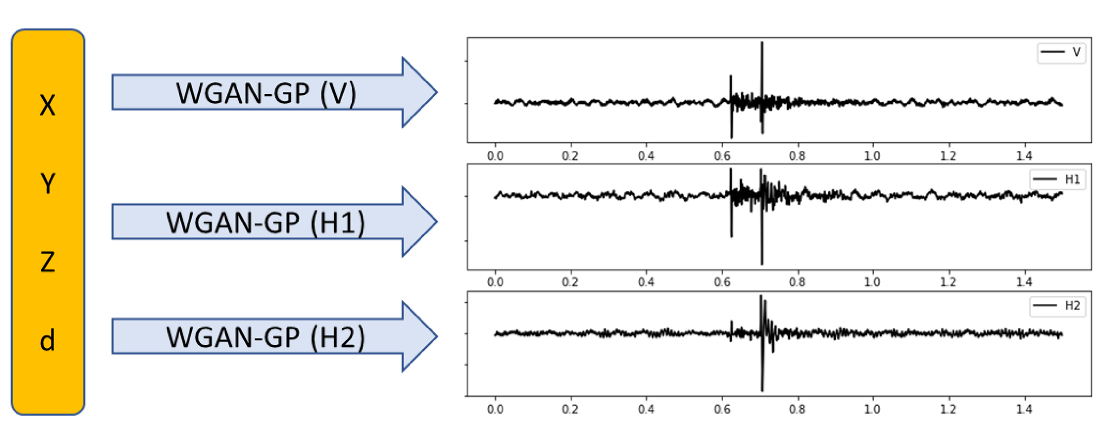


Figure 4. Seismogram generative model using multiple Wasserstein generative adversarial networks with gradient penalty (WGAN-GP). Waveform modulations and phase arrivals assimilate field data well.

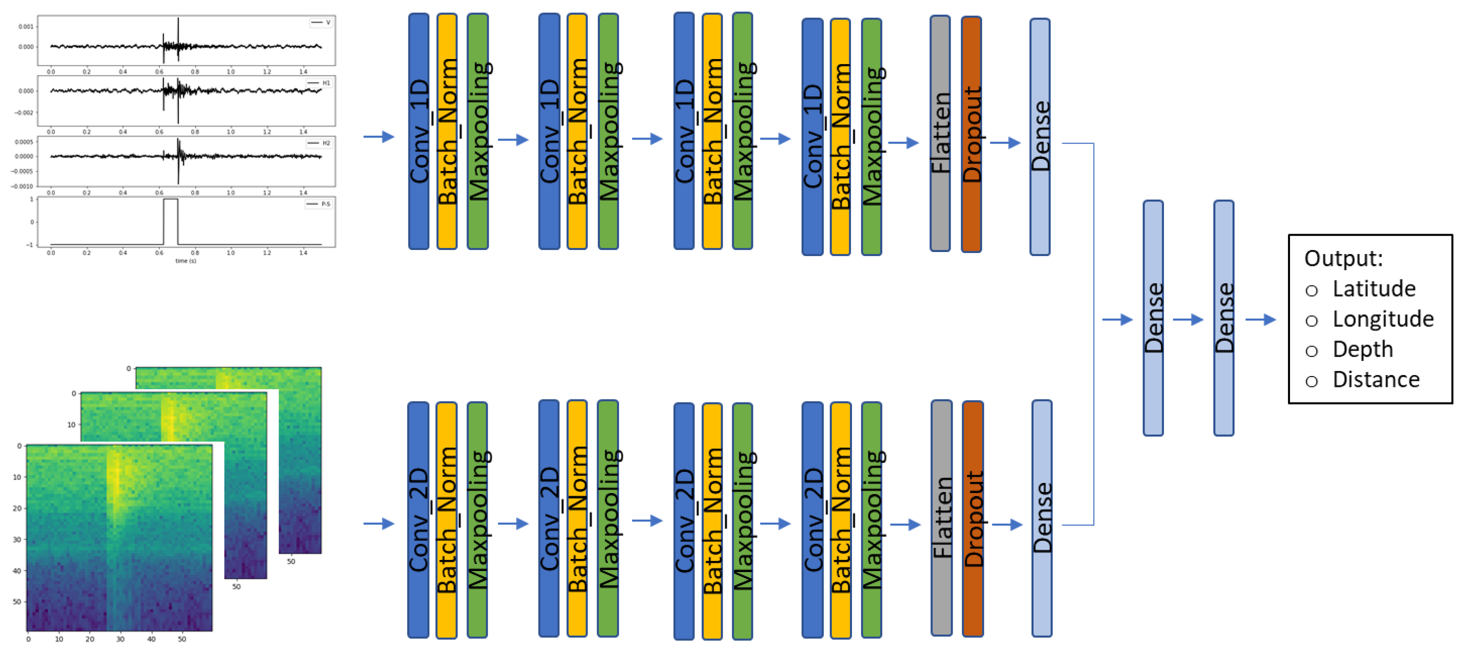


Figure 5. Multimodal CNN architecture for microseismic source location with separate feature extraction pipelines and their input modality.

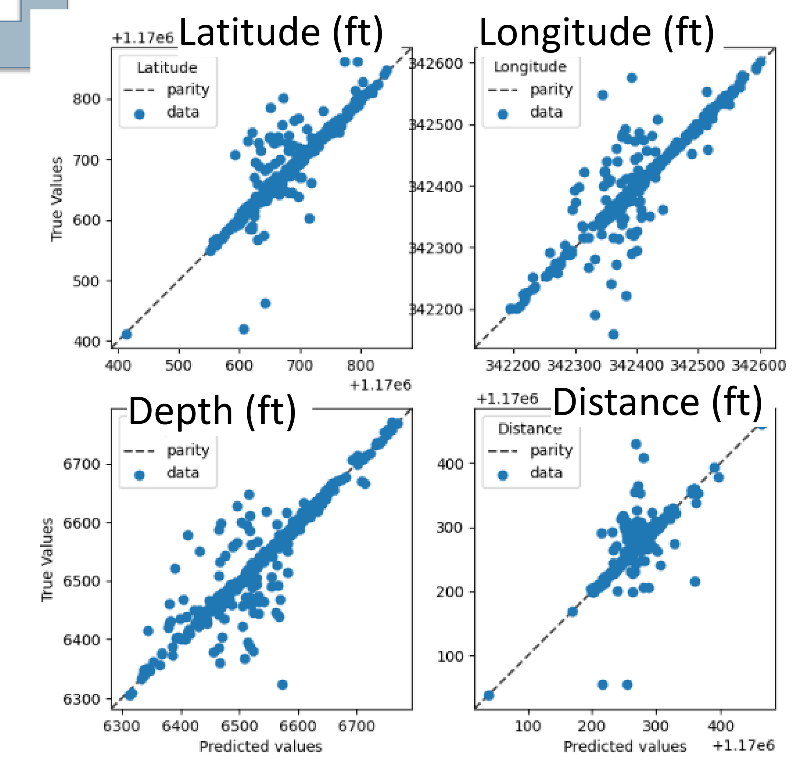


Figure 6. Multimodal CNN model performance of source location coordinates for 2547 samples. Predictions accuracy increased, highly coinciding with true values after augmentation.

Conclusion: Increased event predictions suggest more MS events of interest not registered in the catalog.
Combining WGAN-GP and PhaseNet increased high quality events volume with known P & S phase arrivals.
These four DL models can be integrated to perform rapid source location and fault identification.

References

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3. Spurio Mancini, A., Piras, D., Ferreira, A. M. G., Hobson, M. P., and Joachimi, B.: Accelerating Bayesian microseismic event location with deep learning, Solid Earth, 12, 1683–1705, https://doi.org/10.5194/se-12-1683-2021, 2021.
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