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Improving detection accuracy of microseismic activity during geologic carbon storage using a machine learning method

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Abstract

In this study we implement machine learning approaches for event detection of microseismic activity induced by CO_2 injection at the Illinois Basin Decatur Basin (IBDP) where a number of microseismic clusters are identified. Our primary goal is to improve event detection accuracy and efficiency given a limited number of waveform data. To do this we develop multiple convolutional neural network (CNN) architectures to analyse the spectrogram (i.e., time-frequency images) of the waveforms. The detection results show that the usage of spectrogram and data normalization as a pre-processing enables us to improve detection accurate significantly even with only 600-700 event data per each cluster.

1. Introduction

Due to a growing number of subsurface energy recovery and storage activities over the past decades, induced seismicity has become one of key risk potentials to be controlled and mitigated for sustainable subsurface energy activities. Physically induced seismicity has been attributed to poroelastic response to fluid injection and/or extraction with two primary mechanisms including pore pressure increase and poro-elastic stress transfer (e.g., Chang and Yoon, 2018). Over the past 5 years machine learning/deep learning (ML/DL) models have emerged to improve the detection of seismic events more accurately and efficiently (Perol et al., 2018; Zhu and Beroza, 2019; Mousavi et al., 2020; Münchmeyer et al., 2022). As a recent comparative study of six different DL model for event detection (Münchmeyer et al., 2022) shows that many DL earthquake detection models have shown promising performance for a variety of large magnitude events, the dataset used in evaluation is from seismic data at large scales. Hence, microseismic level events, such as those induced by CO_2 injection into the subsurface, remain challenging due to their low event signal energy and a limited number of events.

In this work we develop convolutional neural network (CNN) models to detect seismic events from continuous waveform data measured at the Illinois Basin Decatur Project (IBDP) site where CO_2 injection has been performed for geologic carbon storage (GCS). In particular, we evaluate the data preprocessing to improve event detection using CNN models and the impact of additional physical properties on event detection accuracy. We will highlight the importance of data preprocessing on event detection for the limited dataset and the improved detection accuracy with additional physical property.

2. Methodology

In this study, we analyze microseismic waveform data obtained at the IBDP site (Will et al. 2016) where ~ a million tonnes of CO_2 have been injected into the lower Mt. Simon formation for 3 years (2011-2014). The detailed data acquisition is reported in Will et al. (2016) and a recent analysis in Williams-Stroud et al. (2020) shows how microseismic events can be used to identify the fault characteristics. For ~3 years injection period, more than 6,000 microseismic events have been detected at 2,000 Hz frequency through two geophones in the reservoir formation and 28 multiple geophysical monitoring geophones. One challenge to analyze the IBDP waveform data stems from the vertical alignment of the sensors, resulting in a very limited surface coverage. Furthermore, there is a very limited amount of event data compared to other repositories. Here, we report our DL models with continuous microseismic waveform data over a short time period (Feb. 27, 2012 to Mar. 12, 2012), totaling to event 612 samples as shown in Figure 1. For event detection we used three channel waveform data from the lowest geophone where signal to noise quality is the best.

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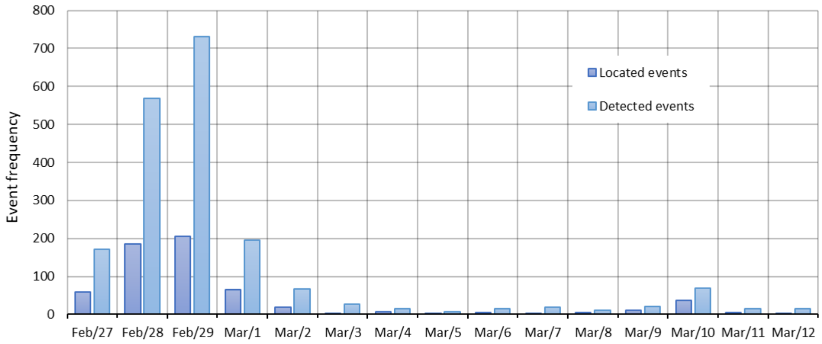

Figure 1. Chronological frequency of event occurrence in daily (24-hour) bins. Detected events represent event identified with traditional phase picker (e.g., STA/LTA) and located events represent the source location of events identified with further analysis (e.g., Will et al., 2016; Williams-Stroud et al., 2020).

With a limited number of waveform samples the models consist of simple CNN architectures with a relatively low number of trainable parameters to avoid overfitting. An overall schematic of our DL models is shown in Figure 2a. The original three channel waveform data (2 second windows at 2,000 Hz) are bandpass-filtered (10-400 Hz) and detrended prior to applying short time Fourier transform for each channel, producing 60x60x3 input samples. Finally, these spectrogram images are normalized by log scaling (Dennis, Tran, and Li 2010) and linearly converting the resulting data values to a range of 0 to 1. We also incorporate a physical property and constraint to improve learning efficiency. In this case we use Mel-Frequency Cepstrum Coefficients (MFCC) as a physical property to represent an energy of seismic event. The MFCC is used as an input to a multilayer perceptron (MLP) which extracts features from additional MFCC. The features from both CNN and MLP are concatenated to train the DL model.

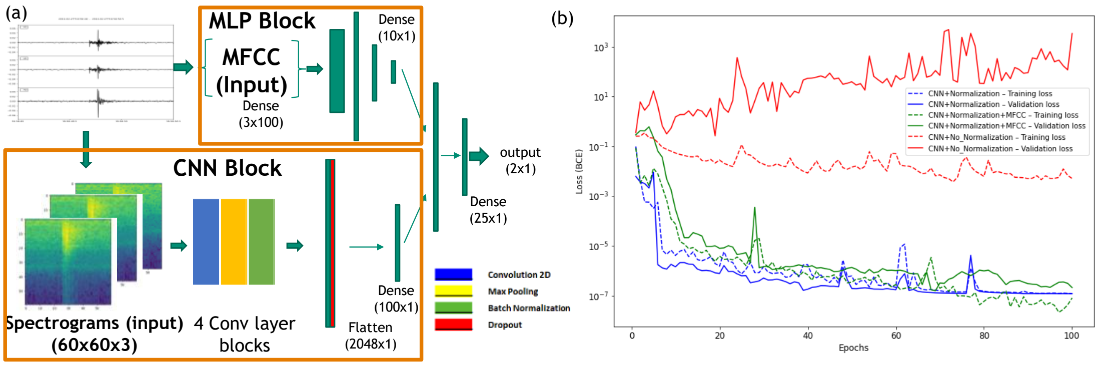

Figure 2. (a) A schematic of DL model architecture. The inputs are 3 channel spectrogram images for the CNN block and MFCC coefficients for the MLP block . The MLP pipeline, shown in the red box, operates in parallel to the base CNN pipeline. Features extracted by both pipelines are concatenated before entering a final dense layer leading to the final prediction output. (b) Binary cross-entropy loss values over epochs for each DL model. Dashed and solid curves represent training and validation loss values, respectively.

3. Results

As seen in Figure 2b, two CNN models with data normalization as the preprocessing were trained excellently and the best models selected have a loss value at an order of $\sim 1\times10^{-6}$. One notable difference between these two models is the CNN model without MFCC input shows an early plateau compared to the CNN+MLP model with MFCC input, and the latter has a better the loss value for validation datasets than for training dataset. The result of the CNN+MLP model may reflect that the addition of physical property of each waveform can be generalized better (i.e., less overfitting to the training data). As described earlier, the IBDP site does not have a large number of event data for training, hence, we include the train results of the CNN model to highlight the impact of normalized input spectrograms on model accuracy, given that higher loss and higher difference between training and validation loss values signifies bad model optimization.

To show that our DL models have learned to distinguish microseismic event features for high fidelity event detection, the trained model is applied for raw continuous waveform data. Input to the trained model is preprocessed in the same way as described previously. We select three day-long (24 hrs) waveform data. Two of these dates have been used to make some training samples as event and noise data for our DL models and are included to identify new microseismic events during these times which are not recorded in the original catalog. On the other hand, one day-long data corresponds to a time period outside of that used for the training data, allowing us to assess our models' capability of generalizing detections for unseen data samples. Table 1 shows event detection results and number of documented events by the catalog for the respective dates.

Table 1. Comparison of number of events reported in the IBDP catalog and events predicted with DL models in this study. Three independent days are selected for comparison, two of which are part of the training data period and one outside of this period.

	Date	Located/Detected	CNN	CNN+MLP
Case 1	Feb/27	60 / 171	203	209
Case 2	Mar/1	66 / 196	532	987
Case 3	Jun/26	64 / 195	174	189

Detection results demonstrate the effectiveness of our DL methodology for microseismic applications. Both DL cases show to be able to detect close to as many or more events than those reported in the IBDP catalog for the days analyzed in Table 1. Manual inspection confirms all detections show seismic anomalies of interest. Figure 3 shows examples of event predictions including events registered in the catalog (on the right side) and new unregistered events (left side).

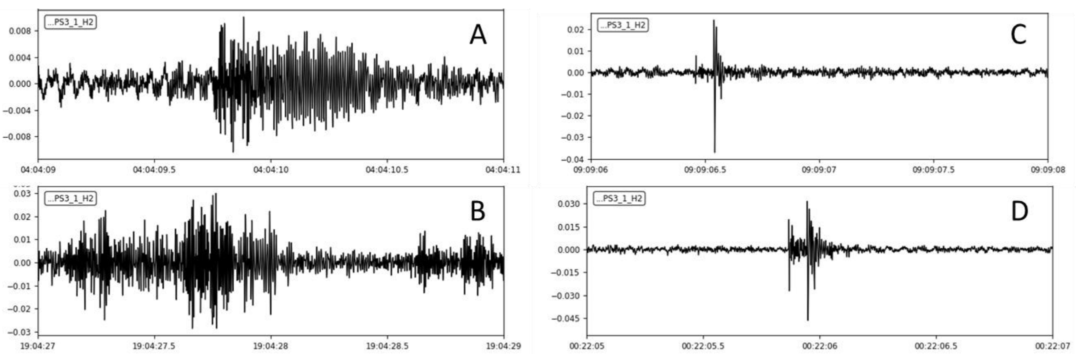

Figure 3. Samples of microseismic events detected by DL models on continuous waveform data. Two samples on the right and left sides are registered and not registered in the IBDP catalog, respectively. Only the horizontal (H2) channel out of the three channel data is shown.

4. Conclusions

We design and compare multiple CNN models with time-frequency feature extraction capabilities for the role of automated high fidelity microseismic event detection, using the IBDP data repository. A crucial aspect of our CNN design is the augmentation of the data time series into a time frequency domain and a proper normalization strategy for the input information, which proved to help optimize our DL models. We demonstrated that presenting additional data driven inputs in a different format (here we use MFCC features) using a simple MLP model in parallel to the CNN model can help improve final decision making for sample classification. This CNN+ MLP model achieves similar optimization performance as the simple CNN for 100 epochs, but its learning progression suggest the CNN+MLP models has potential to improve with further training. Both DL models are subjected to continuous 24 hor recording to evaluate their performance in comparison to the IBDP catalogue records. Study cases 1 and 2 correspond to time periods where data was extracted to create training data for the DL models themselves, therefore they were expected to perform well. However, the significant increase of predicted events for these cases compared to the catalogue suggest there may be more microseismic events of interest unidentified in the IBDP repository. Case 3, on the other hand, corresponds to data of a time period not used for training data, where our DL models achieved comparable results to the IBDP records demonstrating the prediction reliability of our CNN models. Next steps would be applying the CNN models to make prediction over more IBDP continuous recording to have a broader perspective of our DL model capabilities.

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