Introduction

Whether monitoring hydraulically-stimulated fracture growth, carbon storage or cap rock stability in conventional reservoirs, automated seismic event detection is the vital first step in passive seismic monitoring. Typically the monitoring of these situations runs over long durations with events often below the Signal to Noise Ratio (SNR), making it near-impossible for real-time detection to occur without automation. Therefore, it is vital to have procedures for reliable automatic event detection.

One of the most common techniques for full-field event detection is the Short-Time Average to Long-Time Average (STALTA) method (Allen, 1978). However, for the STALTA method, and most adaptations of it, the parameters require careful setting and are closely linked to the recording conditions requiring resettings should the recording conditions change. Over the years many new approaches have been proposed for event detection, for example: waveform template matching, stacking procedures, and machine learning approaches. These new approaches often proved to be more computationally expensive and time-consuming than traditional detection methods (e.g., Skoumal et al. (2016) and references therein) and therefore are not routinely applied.

Machine learning, in particular deep learning, has had a lot of interest in the recent years across all fields of seismology. Strong potential has been shown in the adaptation of computer vision approaches particularly for seismic interpretation, e.g. Waldeland et al. (2018). In this study we have adapted the popular U-Net architecture of Ronneberger et al. (2015), often used for image segmentation, for passive seismic event detection. Trained on synthetic datasets, the resulting model accurately detects a recorded event observed on a Permanent Reservoir Monitoring (PRM) array with a compute time of 3 seconds for an 8 second window.

Data

Recordings from a North Sea PRM system consisting of 3458 multicomponent sensors has been used in this study. A seismic event has been observed in the data as shown in figure 1, alongside platform noise that arrives approximately half way through the recording.

![Figure 1](image)

**Figure 1** Z-component of an event observed on a North Sea PRM system consisting of 3458 sensors.

Considering only the vertical component, synthetic seismic datasets have been generated from a homogeneous velocity model representative of the field for the training of the network. To develop an approach adaptable to full field monitoring, point source events were generated at random subsurface locations within the rough vicinity of the reservoir with varying frequency contents and phases. Waveforms were
generated using the convolutional model methodology. The synthetic wavefields were combined with a Gaussian noise model whose frequency content matched that of the recorded data, with every traces’ noise energy scaled to match the average energy of that trace in the recorded data prior to the event. The noise is added at randomly chosen SNRs from a positively-skewed Gaussian distribution resulting in more training data at low SNRs than at high SNRs.

The data was bandpassed between 2-20Hz and, to easily conform with the contracting and expanding paths of the UNet architecture, each synthetic observation has been padded with 638 zero-traces to result in an input data dimensions of 4096 time samples-by-4096 traces. The middle column of figure 2 gives an example of generated synthetics.

Methodology

The UNet architecture comprises of a series of layers of convolutional neural networks that are part of contracting path followed by an expansive path (Ronneberger et al., 2015). The UNet built for this event detection procedure consisted of 10 layers, with an initial filter size of 4 increasing 2-fold on every layer, and a dropout of 0.05 applied after every layer. The model was trained on 4000 synthetic data sample, with a further 400 synthetic data samples held out for validation to be performed at the end of every epoch. Trained over 20 epochs, the final validation set had an F1-score of 0.93.

For benchmarking purposes, an STALTA autodetection trigger has been calibrated and applied to the recorded event. The optimum parameters were chosen through a manual investigation, and determined to be: a short-term window duration of 0.1 seconds, a long-term window duration of 1.5 seconds, an onset-threshold: 3.5, and an offset-threshold: 3.

![Figure 2 Insets of the last 800 traces from the array of synthetic datasets with events at a high SNR (top row) and a low SNR (bottom row). The first column shows the normalised data, the second column shows the true labels, the third column show the detection with the UNet procedure.](image)

Results

Figure 2 displays predictions made on newly-generated synthetic data (i.e., unseen during training), and compares the predictions, right column, with the synthetically-generated labels, left-column. The top figure is of an event occurring at a high SNR to the side of the array whilst the bottom figure is of an
event occurring at a low SNR directly below the center of the array. The UNet approach is seen to accurately detect the change in moveout shape of the arrivals across the array.

Figure 3 illustrates the results of the event detection on the recorded seismic data in figure 1. Two key differences are observed between the STALTA detection and the UNet detection. Firstly, there are a significant number of spurious detections present in the STALTA results. The second key difference is how the two approaches handle the presence of platform noise - observed arriving in the centre of the array at a similar time to the microseismic event. The STALTA detection approach detects the platform noises arrival whereas the UNet approach appears unaffected by the presence of platform noise, managing to detect arrivals during the increased noise levels.

![Figure 3](image)

**Figure 3** Event detection (a) STALTA and (b) UNet procedures run on recorded data illustrated in figure 1. (c) and (d) show the STALTA and UNet detections, respectively, for the red box. Whilst, (e) and (f) show the STALTA and UNet detections, respectively, for the blue box.

**Discussion**

A drawback of a number of alternatives to the commonly used STALTA autotrigger algorithm is their computational complexity rendering them impractical for realtime monitoring. Data is processed in ∼ 8 second segments. Benchmarked on a 2.9GHz, 6-core Intel Core i9 machine with 32GM RAM, the detection time is 3 seconds, making this a contender for realtime detection. Future work will incorporate
the UNet detection procedure as a data selector that feeds into a microseismic imaging scheme.

The UNet detection procedure holds two key advantages over the STALTA approach. Firstly, the STALTA approach is highly susceptible to noise and often cannot detect events where the SNR is below 1. As noise varies spatially, the STALTA trigger can struggle on traces with a high noise level, such as those highlighted in the blue box in figures 1 and 3. As the UNet has been trained with a noise model with noise amplitudes scaled across the array to the observed amplitudes then it is more resistant to high noise levels on individual traces.

The second advantage of the UNet approach is that it does not require parameter tuning which is commonly acknowledged as non-trivial with Vaezi and Van der Baan (2015) claiming parameter tuning of STALTA and other similar algorithms to often be “unwieldy and subject to error”. By incorporating a range of realistic noise scenarios within the training datasets, the UNet approach learns to handle various noise scenarios and therefore does not require tuning or retraining when the monitoring environment changes. The current noise incorporation approach assumed noise to be stationary with respect to time. An incorrect assumption as highlighted by the platform noise that begins approximately halfway through the recording in figure 1. Therefore, future work will consider noise modelling methodologies to incorporate spatially and temporally varying noise models into the training dataset to build an even more robust event detection procedure, for example covariance noise modelling (Birnie et al., 2016).

Conclusion

In this paper a novel approach to passive seismic event detection has been proposed leveraging on methodologies from the field of image segmentation. Fully trained on synthetic datasets, the procedure requires no manual annotation of training data. The incorporation of realistic noise into the training dataset has resulted in a detection procedure that shows a high tolerance to the presence of noise. Trained on data with events in random subsurface locations, the UNet detection approach can accurately identify events coming from a range subsurface locations with different moveouts in their arrivals. With a compute time less than half of the detection window and a high resistance to noise, the proposed approach surpasses the criteria to become a realtime monitoring procedure.

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