streams, so we only need to calculate the cross-correlation function on a single data stream and can reduce the complexity of the computation. Next, the fast NCC technique is applied to obtain the NCC coefficient matrix. The NCC coefficient between the template event T and the data $f(t)$ is given as

$$C(u) = \frac{\sum_t \left[f(t) - \bar{f_u}\right]\left[T(t-u) - \bar{T}\right]}{\sqrt{\sum_t [f(t) - f_u]^2 \sum_t [T(t-u) - \bar{T}]^2}} \qquad (3)$$

where $C(u)$ is the NCC coefficient at each point u, T is the template event, $\bar{T}$ is the mean of the template, f_u is the mean of $f(t)$ in the region under the template. In Lewis's technique expressions in equation (3) can be efficiently computed with very few operations so we can speed up the detection process. After that, potential events are triggered and extracted when the NCC coefficient is higher than a user-defined threshold. Finally, quality control of the detection results is performed to remove undesirable events. This step is usually done by manual inspection and classification.

Results, Observations, Conclusions

To assess the detection performance of the proposed fast MF, we have implemented this algorithm on a big microseismic dataset (about 1.2 TB) and compared the detection results with the results obtained from the commonly used method, STA/LTA. The data are microseismicity emitted from 78 hydraulic fracturing (HF) treatment stages in 4 HF wells and are continuously recorded by sensors in both vertical and horizontal monitoring arrays. Figure 1 below shows the map view of the location of the treatment and monitoring wells. We run the STA/LTA with an STA window length being three times the dominant period of the event, an LTA window length being five times longer than the STA window, a trigger threshold of 2, and at least half number of receivers must observe the events. The proposed fast MF is implemented with a threshold of 0.2, and at least half of the number of receivers must see the events. Figures 2 and 3 below show the detection results obtained from both methods for each treatment stage. As we can see from these figures, the number of events obtained from the proposed MF and the STA/LTA in each HF stage is almost the same. After manual inspection and classification, we obtain a total of 21766 excellent events (those having both clear P- and S- phases) from the STA/LTA and a total of 19913 excellent events from the proposed fast MF. Thus, the proposed MF algorithm can detect almost the same number of events as the STA/LTA. However, this method requires less time for the detection process than the STA/LTA. The STA/LTA method is an incoherent energy detector which detects events without knowing information on the signals to be detected; thus, noise such as tube waves, electrical noise, and random noise can be incorrectly considered as potential events (those are false alarms/false triggers). With a threshold of 2, the STA/LTA helps to capture almost the number of true events (those having clear P- and/or S-phases) in the data; however, it has lots of false alarms in the detection results. Due to these false alarms, classifying the detection results in the STA/LTA method is time-consuming. In contrast, the proposed MF detects events based on their similarity with the template events. With the threshold of 0.2, the MF can detect almost the same number of excellent events while having fewer false triggers, which save time in the classification step. Furthermore, the combination of the recursive STA/LTA, multiplexing, and fast NCC computation techniques in the workflow fasters the detection performance of the proposed MF.

In summary, the proposed fast MF algorithm can work well with big microseismic datasets. The algorithm speeds up the detection process by applying the recursive STA/LTA combined with multiplexing and the fast NCC techniques. The workflow is easy to follow with a more superior detection performance (less false triggers and high detection probability) than the commonly used method, STA/LTA. To perform the fast MF efficiently, we recommend using this algorithm for data generated from repetitive sources. If there is high variability in the waveforms, the MF can slow down the processing process as more templates need to be considered. The detection threshold can vary depending on the quality of the data. However, it should satisfy a trade-off between true events, false alarms, and missed events.

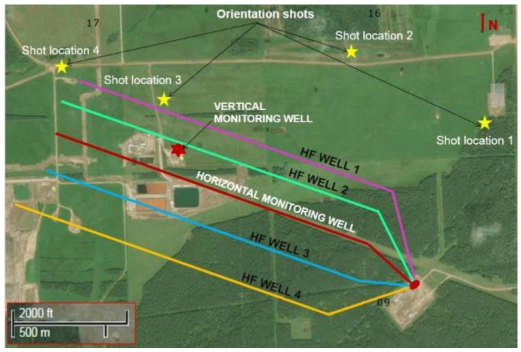
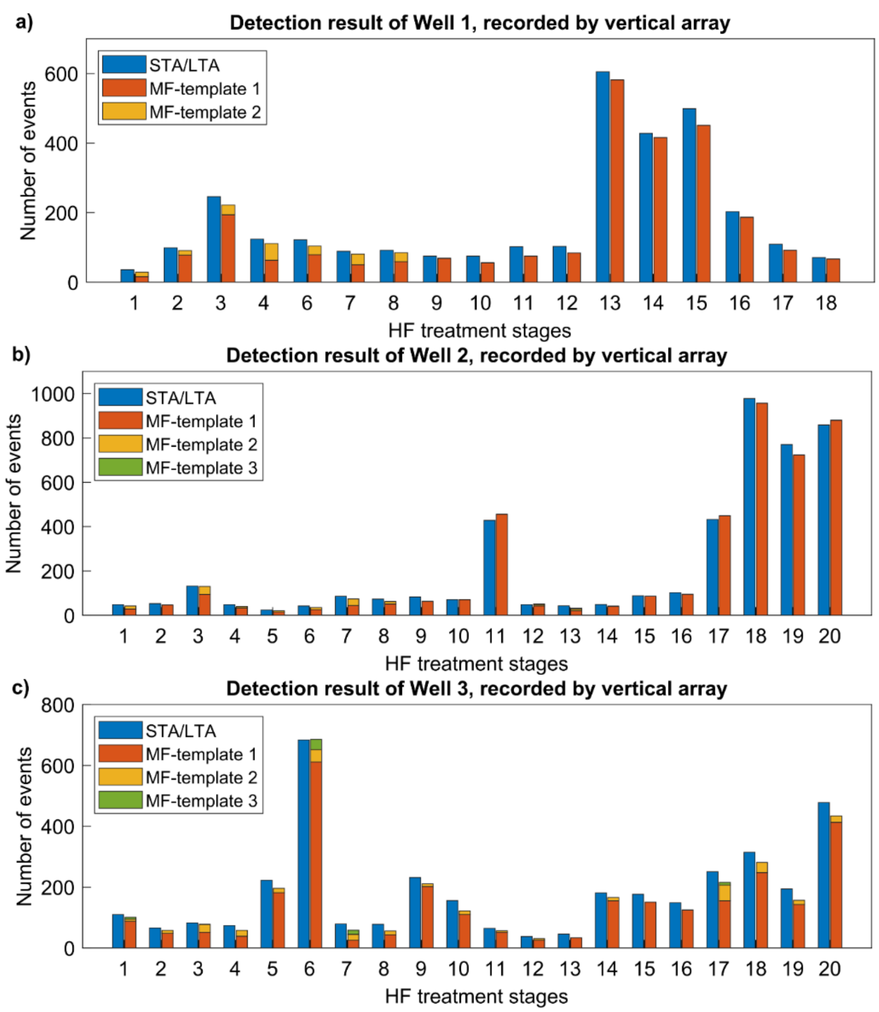


Figure 1 - Map view of the location of the HF treatment and monitoring wells.



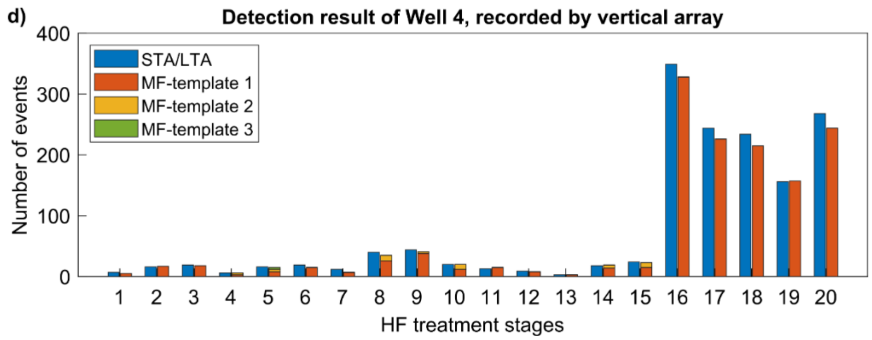


Figure 2 - The detection results of (a) Well 1, (b) Well 2, (c) Well 3, and (d) Well 4, recorded by the vertical monitoring array, obtained from the STA/LTA and the fast MF methods.

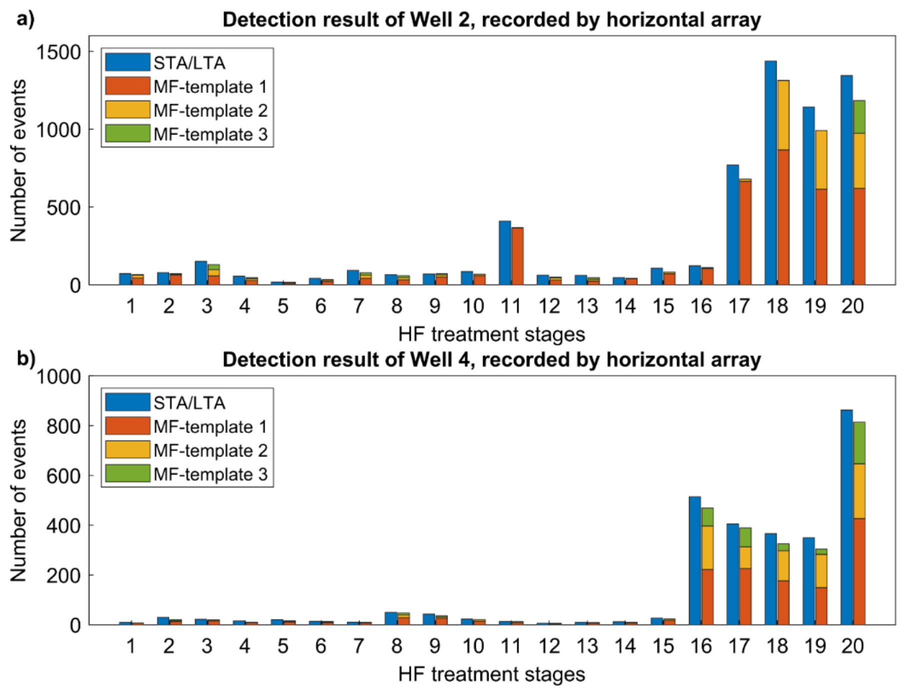


Figure 3 - The detection results of (a) Well 1, (b) Well 2, recorded by the horizontal monitoring array, obtained from the STA/LTA and the fast MF methods.

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