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Application of a fuzzy c-means and AIC based workflow for P/S arrival-time picking on microseismic data

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Summary

Hoadley Flowback Microseismic Experiment (HFME) was carried out in 2012 to monitor an open-hole multi-stage hydraulic fracture treatment in two horizontal wells in the Glauconite zone (Eaton et al., 2014). The downhole microseismic data were recorded using a retrievable array of 12 receiver levels (15 Hz triaxial geophones) in a nearby vertical well. The interpod spacing for the bottom 8 levels and top 4 levels was 15.25 m and 30.5 m, respectively. Here, we present some arrival time picking results on the detected event waveforms from the Hoadley microseismic dataset. In our multi-step semi-automatic picking workflow, we use the unsupervised fuzzy c-means (FCM) clustering algorithm to identify the signal intervals in the event waveforms. For waveforms in these intervals, we pick the arrival times using the Akaike information criterion (AIC) algorithm. We also explain our approach to classify the arrivals as P and S-waves. The focus is more on the workflow performance; therefore, we emphasize the significance of manual intervention to make key decisions. Our workflow accurately picks the arrival times on the waveforms with reasonably good signal-to-noise ratio. However, additional manual quality control effort is deemed necessary to refine picks on relatively noisy waveforms.

Theory

Fuzzy c-means (FCM) clustering

Previously, numerous authors (e.g., Zhu et al., 2016; Gao et al., 2019; Chen et al., 2020; Cano et al., 2021; Lan et al., 2022) have effectively used the fuzzy c-means clustering algorithm for arrival picking on seismic and microseismic datasets. FCM clustering partitions a set of *N* points into *C* clusters by minimizing the objective function (Cano et al., 2021)

$$J(\mathbf{U},\mathbf{V}) \;=\; \sum_{k=1}^{N}\sum_{i=1}^{C}(u_{ik})^{m}\|\mathbf{x}_k-\mathbf{v}_i\|^2, \tag{1}$$

where $\mathbf{U}$ represents the partition matrix whose elements u_{ik} indicate the degree of membership of point $\mathbf{x}_k$ to the cluster i. $\mathbf{V}$ comprises of a set of C points $\mathbf{v}_i$ representing the centroid of the corresponding cluster, and m controls the cluster fuzziness. $\mathbf{x}_k$ comprises of user-defined features computed from the input waveform (e.g., mean, power spectral density).

Akaike information criterion (AIC)

Akaike information criterion (AIC) is another popular algorithm for arrival-time picking on seismic and microseismic datasets (e.g., Oye and Roth, 2003; Akram and Eaton, 2016). Maeda (1985) calculated the AIC values using the following formula:

$$AIC(k) \;= k\,log(var\{x(1,k)\}) \;+\; (N_l \;-\; k \;-\; 1)log(var\{x(k+1,N_l)\})\,, \tag{2}$$

where k ranges between 1 and N_l (length of the input waveform) and var{ x } represents the variance function (Akram and Eaton, 2016). Since the AIC algorithm picks on the global minimum, it works best when only a single instance of the signal is present in the input waveforms. For inputs with multiple signals (e.g., *P* and *S*), it is important to identify the corresponding intervals before applying the AIC algorithm.

Waveform correlation

Waveform correlation is also an effective algorithm for picking and refining arrival times on microseismic datasets. The normalized crosscorrelation of two digital waveforms **x** and **y** can be computed as (Akram and Eaton, 2016)

$$\varphi_{\mathbf{xy}}(\tau) = \frac{\sum_k x_k y_{k+\tau}}{\sqrt{\sum_k x_k^2 \sum_k y_k^2}}, \quad (3)$$

where τ represents the correlation lag. The two input waveforms are considered perfectly identical if $\varphi_{\mathbf{xy}}$ is +1 whereas a value of -1 indicates that the two waveforms are similar but with opposite polarity.

Picking workflow

We pick P and S-wave arrival times using the following workflow:

1. Identify signal intervals in the input waveforms using the FCM clustering algorithm.
2. Determine arrival times in each of the signal intervals using the AIC algorithm.
3. Classify the signals based on the waveform polarization attributes.
4. Refine and eliminate mispicks by applying FCM clustering on the picked arrival times.
5. Perform manual quality control and set criterion to label P and S moveouts.
6. Identify events with similar waveforms using crosscorrelation and repeat the manual quality control of the pick accuracy.

Results and Discussion

Figure 1 shows the examples of arrival-time picking using the steps 1-2 from our picking workflow. In the case of a single arrival (Figure 1a), we can only assign the unknown arrival type (indicated by the green color) after the first two steps in the workflow. Figure 1b shows the example of waveforms containing two arrivals with similar moveouts. In this case, we differentiate between the two arrivals using the polarization angles. However, the results in Figure 1b are not as good as in Figures 1c-d, where both P and S wave arrivals are differentiated correctly. It is important to mention that at this stage, the blue and red colors in Figures b-d indicate only the presence of different arrivals and not specifically the P and S-wave arrivals. In Figures c-d, when only one of the two arrivals are picked for a receiver level, the status changes to the unknown arrival type (green color).

We understand that there may be numerous challenges when picking P/S arrivals on microseismic datasets. However, keeping our focus on the pick results from Figure 1, we observe two main problems including inconsistent arrival types (second arrival, Figure 1b) and unknown arrival types (P/S). To improve the consistency of arrival types, we use the FCM clustering algorithm on the picked arrivals from Figure 1, assuming that there are at most two arrivals present in the analysis window. Figure 2 shows the two distinct clusters (using a threshold of 0.5) for the two arrivals. The distance between the mean values of the two clusters are used to determine whether these represent a single arrival or two different arrivals. Figure 3a shows that the picks for the second arrival have changed to the unknown class since almost the same number of picks belong to both class 1 and 2.

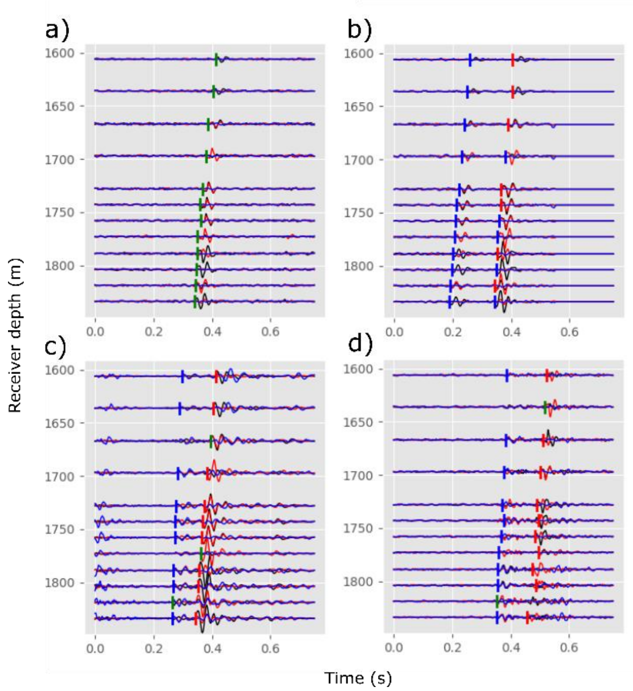

Figure 1: Examples of arrival-time picking using steps 1-2 from the picking workflow. a) single arrival picks b) multiple arrivals with similar moveouts c-d) multiple arrivals (P/S) with distinct moveouts. The green color picks indicate that arrival type is not determined where blue and red, in this phase, only indicate that arrivals are different.

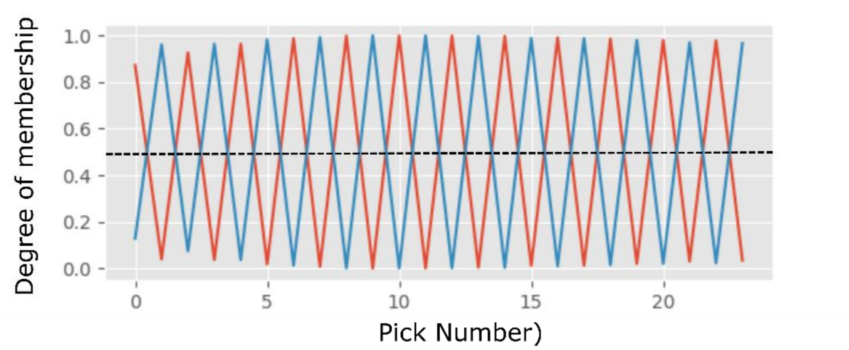

Figure 2: FCM cluster memberships for the arrival picks shown in Figure 1b. The dashed horizontal line represents the threshold value to identify cluster members.

To classify the unknown arrival types into P and S, we compare the moveout of single arrival waveform from Figure 1a with P and S moveouts from Figure 1c. This clearly indicates the arrivals picked in Figure 1a represent the S-wave. After updating Figure 1a, we can update the remaining picks as shown in Figure 3c (both arrivals in Figure 1b also represent the S-wave arrivals from two different events). For more noisy waveforms, manual quality control is important and further criterion are used in the workflow to refine the arrival picking.

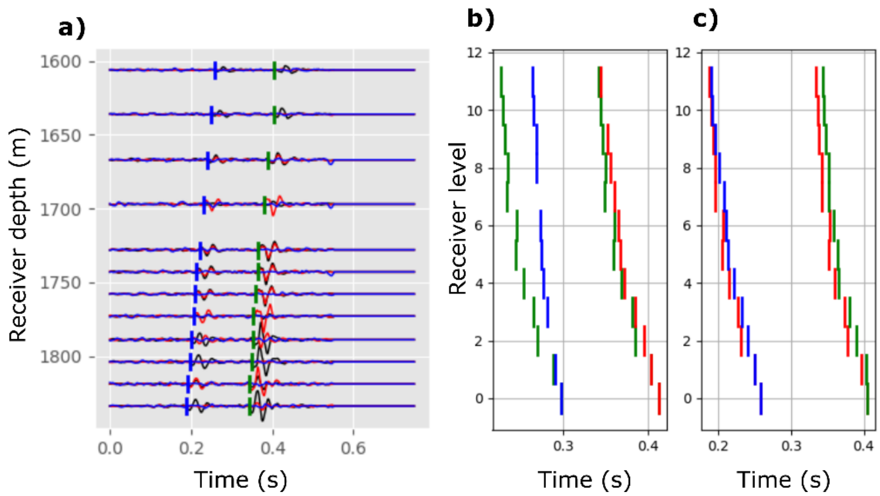

Figure 3: a) Arrival times picked in Figure 1b are refined and reassigned using FCM clustering criterion. b) Arrival times from Figure 1a are compared with P and S moveouts from Figure 1c to identify the corresponding membership. c) Arrival time moveout from Figure 1a after updating the P/S class is compared with moveouts from Figure 1b to update the arrivals class.

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