Probabalistic Clustering of a Discrete Fracture Network from Microseismic Data

Scott H. McKean, Jeffrey A. Priest, Jan Dettmer, David W. Eaton

University of Calgary

Summary

Microseismic monitoring is common in the mining and petroleum industries. Pattern recognition to identify faults, fractures, and damage zones in the microseismic data can be a challenge due to the density and number of observations and their multiple attributes. This study evaluates unsupervised machine learning techniques for identifying a discrete fracture network (DFN) from microseismic dataset that was collected during a hydraulic fracturing program in the Duvernay Formation. It compares partitional, hierarchical, density-based, and finite mixture model clustering methods with multiple subsets of data attributes. The study shows that lower dimensional datasets tend to yield the best results, and that it is possible to cluster microseismic data using finite mixture models. The finite mixture model is applied to a large (n = 12,076) microseismic catalogue and the results appear to reflect the physical mechanisms of hydraulic fracture generation.

Methods

This study evaluates four common unsupervised learning methods for clustering (partitioning, hierarchical, density-based, and Gaussian mixture models), along with correlation and principal component analysis (PCA) for exploratory data analysis. Various subsets of attributes were used along with the four clustering techniques. Partitional clustering techniques, which divide observations into non-overlapping clusters based on their dissimilarity, were evaluated with the K-medoids method. Hierarchical clustering merges observations with the minimal pairwise distance sequentially, until all pairs of clustered are connected agglomoratively. Ward's method was for hierarchical clustering in this study. Density-based spatial clustering with noise (DBSCAN) was used to cluster observations based on their multidimensional density. Finally, a model-based approach with multivariate Gaussian mixture models (GMMs) was also used for clustering. This technique is well suited for DFN identification because it applies a model that automatically accounts for noise, provides a mean and covariance matrix that directly provides the geometry for each fracture, and is able to identify dense lineations.

Results

This study showed that traditional clustering validation statistics aren't readily applicable when identifying a DFN from microseismic data. It showed that multivariate Gaussian mixture models were able to identify a physically plausible discrete fracture network from microseismic data. This DFN showed induced and natural strikes and fractal characteristics. Figure 1 shows an example from a single hydraulic fracturing stage that compares the four methods. The fracture poles from the GMM results on the whole dataset are summarized in Figure 2.

Acknowledgments

This work is funded by the Canada First Research Excellence Fund (CFREF) and NSERC. This work wouldn't have been possible without the donation of high quality dataset by an anonymous producer or the support of the Microseismic Industry Consortium.

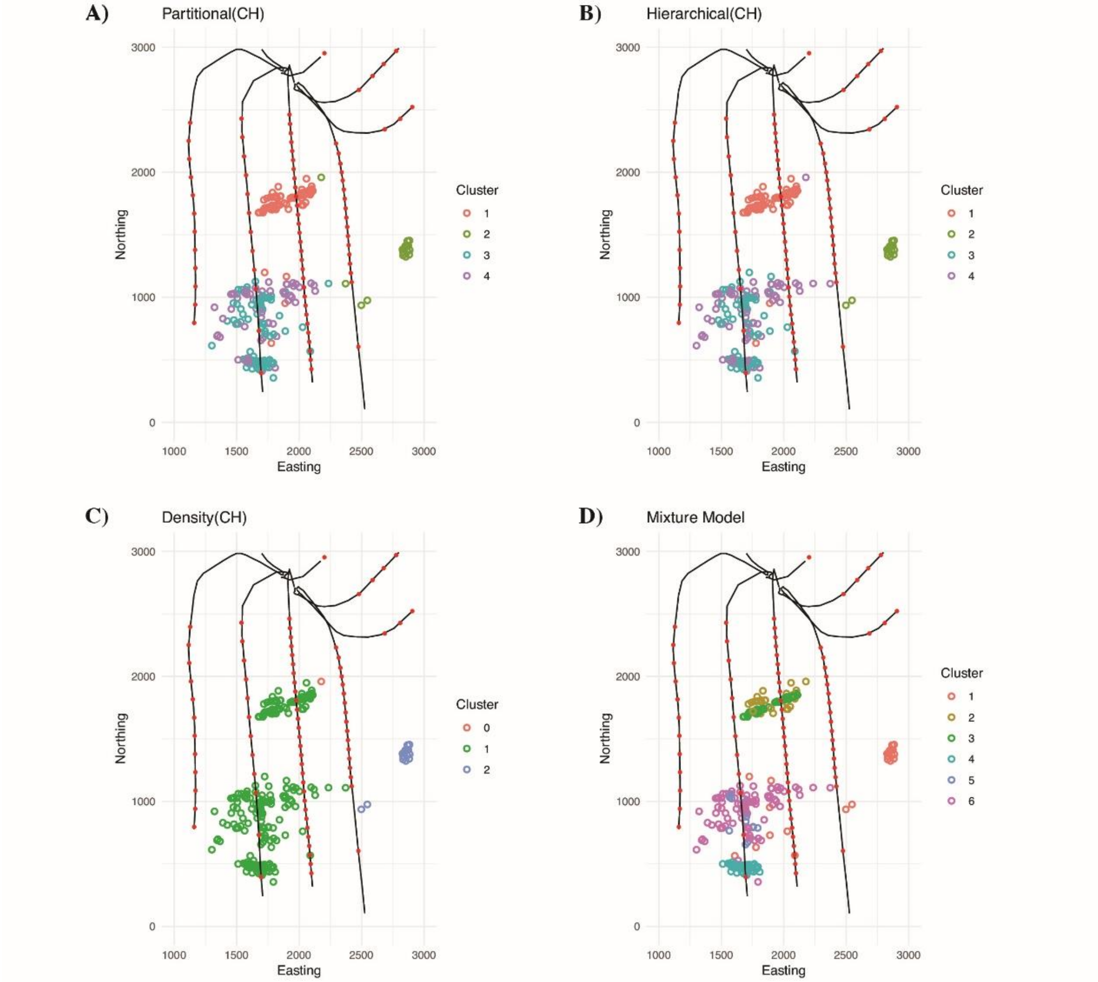

Figure 1. An example of clustering results using a data subset with spatial coordinates and time. The figure shows the clustering resulting from partitional (A), hierarchical (B), and density based (C) clustering, as well as the results from gaussian mixture model clustering (D). The resulting clusters are differentiated by colour. Note the two lineations identified by the mixture model.

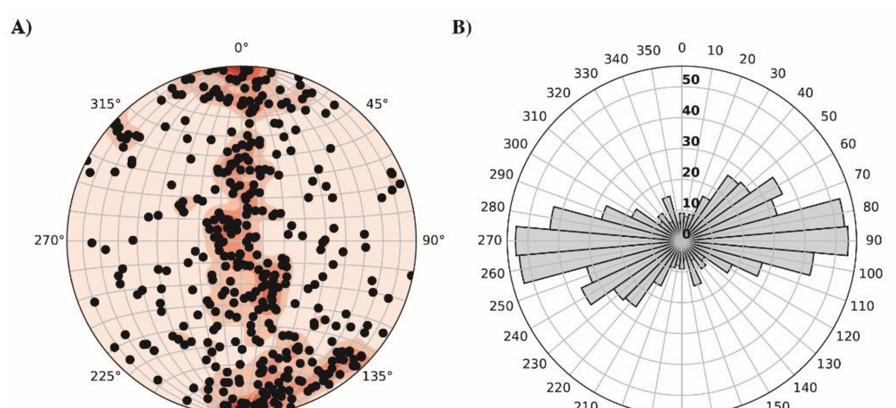

Figure 2. (A) An Equal area stereonet showing the density plot of poles for 406 clusters identified by the GMM algorithm (contours represent two standard deviations). (B) A rose diagram of the fracture plane strikes, showing a strong tendency for strikes of 90 and 270 degrees.