Graph theoretic network mapping of rock fracture networks for mechanism classification using machine learning techniques

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Fracture networks in rocks display many characteristics, which often give information about the mechanisms by which they were formed. For example, the volume-increasing and volume-decreasing nature of hydration and dehydration reactions respectively, produce distinctly different network features including regular, polygonal, fracture-bounded regions in the former and dead-end branching from existing fractures in the latter (Okamoto and Shimizu, 2015). These characteristics and mechanisms are important for understanding the complex geological and chemical phenomena which produce them. Other investigators have used heterogeneity and topology measures to classify and recreate such networks (Hafver et al, 2014), but we believe that graph theoretic networks offer a rich and natural analogue by which fracture networks may be explored and classified, as other authors have already pointed out (Gaffari et al 2011, Estrada and Sheerin, 2017)

Network graphs are defined by a set of nodes that are connected by edges or links. These edges may be weighted depending on the nature of the relationship being represented. It is possible for example, that edges in a fracture network may be weighted by the length of the fracture, the aperture, surface roughness, etc. depending on the classification purposes of the investigator. In this work, we define nodes to be either a) the junction point between 2 or more intersecting fractures, or b) the terminal point of a fracture, in cases where said fracture does not terminate at another fracture (t-junction). By creating graph networks from fracture networks, we can take advantage of the well-developed metrics of graph theory in order to classify these fracture networks according to their mechanistic and structural features. Among these graph theoretic metrics are measures of cohesiveness (density, transitivity, geodesic distance, etc.), measures of centrality, or the relative impact that each node has on the overall structure (eigenvector, closeness, betweenness, etc.), and spatial distributions or grouping (clustering, core-periphery, etc.). The choice of measure to be used must be carefully considered, as some measures relate to specific circumstances, and may not be appropriate outside of the applications for which they were designed (Borgatti 2005). Using these measures, it is possible to broadly classify structures as belonging to a major structural type, such as scale-free (characterized by a power-law degree centrality distribution), random (characterized by a regular distribution of links among nodes) and small worlds (characterized by the ratio of the distance between nodes to the log of the number of nodes in the network). Classifying fracture networks using these metrics will give us information about the scalability of their mechanisms and features, as well as the efficiency with which the fracture networks can transport reactants for further reaction and fracturing.

The final goal of this research is to create a machine-learning algorithm which may identify network characteristics, which it will then use to classify the network according to the probable mechanism that created it.

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