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Directional semivariogram analysis to identify and rank controls on the spatial variability of fracture networks



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A R T I C L E I N F O

ABSTRACT

Keywords: Semivariogram Fracture Fault Fold Arches National Park In this study, the directional semivariogram is deployed to investigate the spatial variability of map-scale fracture network attributes in the Paradox Basin, Utah. The relative variability ratio (R) is introduced as the ratio of integrated anisotropic semivariogram models, and R is shown to be an effective metric for quantifying the magnitude of spatial variability for any two azimuthal directions. R is applied to a GIS-based data set comprising roughly 1200 fractures, in an area which is bounded by a map-scale anticline and a km-scale normal fault. This analysis reveals that proximity to the fault strongly influences the magnitude of spatial variability for both fracture intensity and intersection density within 1–2 km. Additionally, there is significant anisotropy in the spatial variability, which is correlated with trends of the anticline and fault. The direction of minimum spatial correlation is normal to the fault at proximal distances, and gradually rotates and becomes subparallel to the fold axis over the same 1–2 km distance away from the fault. We interpret these changes to reflect varying scales of influence of the fault and the fold on fracture network development: the fault locally influences the magnitude and variability.

1. Introduction

In geological systems, a homogeneous material comprises uniform attributes over a given spatial domain (e.g., density, porosity, permeability, elastic moduli). Although the properties of natural geological systems are rarely, if ever, homogeneous, the classification of something as such is often useful. For example, spatial homogeneity greatly simplifies mathematical formulations of heat transfer, fluid flow, and linear elasticity (e.g., Pollard and Fletcher, 2005; Fairley, 2016). However, the application of these mathematical models to natural systems requires the qualification that homogeneity is assumed over an appropriate support scale (Rubin, 2003). This support scale is defined on the basis of statistical homogeneity or macroscopic averaging, in which the variability of a material property converges on an expected value over a range of length scales, commonly called the continuum scale (Guéguen and Palciauskas, 1994).

In the field of geostatistics, spatial variability is a concept that describes how measurable attributes vary in the spatial domain (Deutsch, 2002). At a given scale, a perfectly homogeneous system has zero detectable spatial variability, which means the measurable value for a given material property will be the same at all positions within the

domain of interest. By comparison, heterogeneous systems will display some detectable and non-zero amount of spatial variability at a particular scale. Geostatistics provides a set of tools to quantify the attributes of spatial variability, including its structure, magnitude and directional dependence (anisotropy), as well as systematic methods for modeling spatially variable system attributes (Kitanidis, 1997; Deutsch and Journel, 1998; Deutsch, 2002).

A fractured volume of rock is an excellent example of a spatial domain comprising attributes that often display a significant degree of spatial variability. Examples of these attributes include fracture length per unit area, fracture area per unit volume, number of fracture intersections per unit area or volume, and fracture orientation; all of these attributes could vary from place to place throughout a fractured rock mass, and in ways that are imperceptible to the naked eye. Quantitative characterization and analysis of the spatial variability of these and other characteristics of fracture networks has a wide range of industrial applications because fractures reduce the structural integrity of materials, create conduits and barriers that can enhance or impede subsurface fluid flow, and can impact how subsurface data are either collected, interpreted or predicted. In general, quantitative fracture network characterization has traditionally been investigated using 1-D

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scanline methods; however, recent advances in fracture network data acquisition (e.g., remote sensing, microseismic) have made it possible to examine the spatial attributes of fracture networks on the basis of data-intensive 2- and 3-D geostatistical methods.

1.1. Fracture network characterization using scanlines

Field structural geologists most often characterize fracture networks (Sanderson and Nixon, 2015) using 1-D scanlines that are oriented perpendicular to a fracture set of known orientation, timing, mode, or filling (Watkins et al., 2015). Along a scanline, geologists record the location of each fracture intersecting the scanline, as well as other attributes of interest, such as aperture for joints, throw for faults, or the degree of fracture mineralization. Scanlines are a common method for fracture data collection because they are easily employed on vertical and horizontal outcrop surfaces of limited extent, and because they yield data that are similar to that collected along boreholes.

Many workers have used scanlines to analyze the *statistical distribution* of sampled fracture attributes like height (Bisdom et al., 2014), aperture (e.g., Gudmundsson et al., 2001; André-Mayer and Sausse, 2007; Hooker et al., 2013; Santos et al., 2015), spacing and throw (e.g., Gillespie et al., 1993; Ortega et al., 2006; Putz-Perrier and Sanderson, 2010; Soden et al., 2016). These studies often have one or two aims: (1) to establish mathematical relationships that facilitate the prediction or modeling of fracture attributes, or (2) to elucidate how the processes of fracture initiation, growth, interaction, arrest and mineralization might lead to an observed attribute distribution (e.g., Olson, 2004; Fischer and Polansky, 2006; André-Mayer and Sausse, 2007; Hooker et al., 2013).

To investigate the spatial distribution of fractures or fracture attributes, workers typically plot the value or cumulative value of an attribute along a scanline (e.g., Putz-Perrier and Sanderson, 2010; Riley et al., 2010; Hooker et al., 2013; Rotevatn et al., 2013; Sagi et al., 2016), or calculate the coefficient of variation (C_{ν}) for all the attribute values collected along a single scanline (e.g., Gillespie et al., 1999, 2001; André-Mayer and Sausse, 2007; Deng et al., 2013; Hooker and Katz, 2015; Wennberg et al., 2016). Although these approaches are typically used to quantify the degree to which fractures are randomly distributed or clustered along the scanline, they are more accurately described as measures of sample variability, not spatial variability. Recent work by Li et al. (2017) and Marrett et al. (2017) eliminates these shortcomings by using a normalized correlation count method to more precisely assess the manner and degree to which fractures are spatially correlated. Unlike C_{v} -based approaches, their method can assess spatial variability because it incorporates the sequence of fracture spacings along a scanline. To document directional or large-scale variations in fracture attributes, such as those that might occur in kilometer-scale folds or near faults, geologists typically use multiple scanlines of different orientation and/or location (e.g., Berg and Skar, 2005; Laubach et al., 2014; Watkins et al., 2015; Choi et al., 2016; Cilona et al., 2016). These approaches cannot directly characterize the manner in which fracture or fracture network properties change between scanlines or in directions that are not parallel to a scanline.

1.2. Fracture network characterization using geostatistics

While it is convenient to categorize the abundant scanline-based studies of fracture networks as "geostatistics", this term is more appropriately reserved for the suite of spatial statistical tools that are based on the Theory of Regionalized Variables (Matheron, 1963). In this context, Matheron (1963) defined a regionalized variable (RV) as having three primary attributes: (1) the RV is localized such that variations occur over a geometrical space or "support scale"; (2) the RV is

characterized by variable spatial continuity with the extreme case of no spatial continuity defined as the "nugget effect"; and (3) the spatial continuity of a RV may exhibit directionality (i.e., anisotropy). Further discussion of the RV construct is presented in Appendix A.

The concept of spatial continuity is rooted in what is often referred to as the first law of geography, which states that attributes separated by short distances are more related than those separated by long distances (Tobler, 1970; Miller, 2004). In general terms, the presence of spatial continuity implies a degree of spatial correlation. Unfortunately, the terms spatial continuity and correlation are often used synonymously with spatial variability, creating a dangerously misleading equivalence. For example, a RV with non-zero variance exhibits spatial variability; however, the spatial continuity (i.e., spatial correlation) depends on whether or not the value of the RV is dependent on separation distance. As a result, spatial variability can exist in the absence of spatial continuity, whereas the absence of spatial variability (i.e., homogeneity) ensures maximum spatial continuity.

Geostatistics provides a means to describe and quantify the spatial continuity of physical phenomena (Isaaks and Srivastava, 1989) and has been used in fields ranging from geology to meteorology, biology, agriculture and public health. Kriging, sequential simulation, and semivariogram analysis are among the most widely used geostatistical tools, and there are numerous examples of geostatistical analyses of fracture networks (e.g., Gervais et al., 1995; Viruete et al., 2003; Sisavath et al., 2004; Neuman, 2005; Dowd et al., 2007; Rafiee and Vinches, 2008; Dewit et al., 2012; Koike et al., 2015). The concept of spatial anisotropy has proven particularly useful for understanding and modeling fluid flow in fractured geological media. For example, Pollyea and Fairley (2012) invoked geostatistical methods to quantify the anisotropic nature of fracture occurrence in basalt outcrops, and then implemented semivariogram analysis and sequential indicator simulation to develop equally probable, but spatially variable reservoirs for modeling CO₂ sequestration in basalt formations. Similarly, Pollyea et al. (2013) invoked the semivariogram of fracture occurrence to optimize spatial sampling patterns for fractured basalt characterization, and Pollyea and Fairley (2011) implemented semivariogram analysis on LiDAR scans of basalt outcrops to illustrate that discrete fracture networks can be extracted as second-order information from a LiDAR point cloud. In contrast to techniques that rely on scanlines and the coefficient of variation, geostatistical tools like the semivariogram do quantify the spatial continuity and variability of regionalized variables. These tools also enable users to identify trends in spatial continuity, and to recognize the distances over which spatial correlation ends and statistical randomness begins.

In this paper, we use semivariogram analysis to characterize and quantitatively compare the amount and style of variability displayed by a natural fracture network that is exposed in the footwall of a kilometerscale normal fault that formed in the limb of a map scale anticline. Our aim is to understand the relative role these structures played in controlling the spatial variability of fracture network properties. We specifically focus on the spatial variability of fracture intensity and intersection density as these are proxies for secondary porosity and permeability, and as such, are indicators of the efficiency of fluid storage and flow through fractured rock masses (Rohrbaugh et al., 2002). Determining the magnitude and correlation structure of spatial variability displayed by this fracture network allows us to infer the geological or geomechanical causes of the variability, and provides quantitative information that can be included in predictive, stochastic models of spatially varying fracture, and fracture network properties.

2. Geological background

We examined the fracture network in a roughly 2.5 km² area of

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