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Correlation Analysis of Fracture Intensity Descriptors with Different Dimensionality in a Geomechanics-constrained 3D Fracture Network

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Summary

3D intensity parameters of fracture networks cannot be measured directly and are usually correlated with the lower dimensionality intensity parameters, such as P21, P10. A comprehensive correlation analysis between lower dimensionality measures, P10, P20, P21, I2D (total number of intersections per unit area) and higher dimensionality ones, P30, P32, I3D (total number of intersections per unit volume) are investigated. We also correlate small cube samples and underlying fracture networks that represent cores or tunnels. The fracture networks are constrained by geomechanics principles and outcrop data to make them geologically meaningful. We show that orientation of fracture samples impacts correlations between the 2D and 3D parameters and samples parallel to the principal stresses yield better correlations. 3D intensity parameters, P30, I3D, and P32 can be predicted from 2D or small cube samples. However, 1D intensity P10 doesn't have a strong correlation with 3D intensity parameters. The size of cube samples should be larger than 10 percent of the original size to capture main structural information. Furthermore, the minimum number of samples to reach a good correlation from 2D and cube samples are 20 and 60 respectively.

Introduction

The knowledge of fracture sizes, shapes and connections is necessary to describe “intensity” of a fracture network. Dershowitz (1992) defined the fracture intensity measures in different dimensions, denoted as P_{ij} , where i refers to the dimension of the sample and j refers to the dimension of the measure. For example, P_{10} is the number of fractures per unit length and P_{21} is the length of fracture traces per unit area, etc. Available measures are usually 1D and 2D, e.g., P_{10} from image logs, P_{20} and P_{21} from outcrop studies, etc. However, the real fracture networks are 3D and their intensity cannot be measured directly. The 3D intensity parameters are crucial in many engineering applications, and it is necessary to find correlations between the lower dimensionality measures and the higher dimensionality ones, if these correlations exist. Dershowitz et al. (2000) found that the 1D intensity measure P_{10} and the 2D measure P_{21} are often linearly correlated with the 3D intensity measure P_{32} . Wang (2005) found that P_{10} and P_{32} have a linear correlation under certain assumptions about the distributions of fracture lengths, positions and orientations. Comprehensive analysis of fracture intensity parameters in different dimensions is rarely possible, mostly because of insufficient data. Since real fracture networks are complex and their geometry and topology are poorly known, it is impossible to model these networks exactly. Therefore, stochastic fracture networks are the only practical alternative (Zhu et al., 2018). With our algorithms, we can generate arbitrary stochastic fracture networks in 2D and 3D. These networks may follow any distribution of fracture lengths, orientations, and positions of fracture centers. Our networks can be investigated systematically for the correlations between the 1D and 2D intensity measures, and the 3D measures. In this work, we generate a typical fracture network constrained by geomechanics and outcrop data, which includes four types of joints. Then we conduct the scanline surveys and cross-section surveys to investigate correlations between lower dimensionality measures, P_{10} , P_{20} , P_{21} , and the higher dimensionality ones, P_{30} and P_{32} . Since percolation in a fracture network depends on fracture intersections, we also include the intersection density, which is defined as the total number of intersections per unit area in 2D, I_{2D} , or the total number of intersections per unit volume in 3D, I_{3D} . Finally, we investigate the correlations between small cube samples and the original 3D fracture networks. These samples correspond to cores or tunnels.

Correlation analysis of different intensity parameters in geomechanics-constrained fracture networks

In this paper, we constrain fracture networks with simple geomechanics principles and outcrop characteristics to make them more geologically meaningful. To this effect, we have introduced four types of joints, sketched in **Fig. 1a**. Type 1 joints are in blue and type 2 joints are in green. These are tension joints that are, respectively, approximately parallel and perpendicular to the hinge line. The Type 3 conjugate shear joints (actually microfaults) are in red. They have dihedral angles equal to 60° and their angle bisectors are parallel to the maximum principal stress σ_1 . Type 4 shear joints (microfaults) are in cyan. They have random strikes and dips because of the local anisotropy. The existence of random shear joints brings more complexity and uncertainties to the network. The system size in this paper is 100^3 of arbitrary units. The orientations of the maximum and minimum principal stress σ_1 , σ_3 are north-south and east-west, respectively. The distributions of fracture lengths, strike angles, dip angles and the positions of fracture centers are listed in **Table. 1**. The minimum length of fracture L_{min} used in a power law distribution is 3 initially. When a spanning cluster is formed in the system, L_{min} reduces to 1.5 and the probabilities for type 3 and 4 joints increase to 0.43 and 0.53. After a spanning cluster emerges, the pore pressure propagates across the system, makes the local stress field more complex and easier for shear failures. Therefore, it generates smaller secondary joints and more random shear joints. **Fig. 1b** is an outcrop map cited from Holland et al. (2009), and the joint intensity is far beyond the percolation threshold. Therefore, the termination criterion in our model is a number of total fractures randomly distributed in $[45000, 55000]$, which is about 10 times larger than the percolation requirement. **Fig. 1c** is a cross-section map of our fracture network. **Fig. 1b** and **c** are not identical, but they share many common characteristics, like preferential fracture orientations, different fracture sets, etc. We generate 100 stochastic fracture networks and calculate the P_{30} , P_{32} and I_{3D} for each one of them. After that, we take 100 scanline samples and 100 cross-section samples, respectively, in each 3D fracture network, calculate the corresponding parameters, P_{10} , P_{20} , P_{21} and I_{2D} , and average them. The

Table 1 Distributions of each type of joints.

Type of joints	Probability ^a	Center position	Strike	Dip	Length
1	0.02	Uniform ^b	von Mises-Fisher ($\mu = 90^\circ, \kappa = 300$)	90°	2L
2	0.02	Uniform	von Mises-Fisher ($\mu = 0^\circ, \kappa = 300$)	90°	Power-law ^e ($L_{max} = L, a = 3$)
3	0.72	Uniform	^d N60°E, S60°E	90°	Power-law ($L_{max} = L, a = 2.5$)
4	0.24	Fractal ^c	Uniform ($[0, 2\pi]$)	Uniform ($[0, 2\pi]$)	Power-law ($L_{max} = L, a = 3$)

^a probability of generation.

^b a uniform spatial distribution.

^c a fractal spatial density distribution and the fractal dimension is 2.5 in this research.

^d the dihedral angles equal to 60° and angle bisectors are parallel to σ_1 .

^e L_{max} is the maximum length of the fracture; a is the exponent of the power-law distribution.

orientations of the scanlines and cutting-planes are either uniformly distributed between $[0, 2\pi]$ or are orthogonal to principal stresses. In each 3D fracture network, we take 100 small cube samples. The sample sizes vary between 1 and 35 percent of the system size. We calculate the intensity parameters in the cube samples, denoted as P_{30s} , P_{32s} and I_{3Ds} . **Fig.2** is a sketch map of the different samples from the fracture network.

Figure 1 **a:** A sketch map to illustrate four types of joints in a fold structure; **b:** An outcrop map from Holland et al. (2009); **c:** A cross-section map of our fracture network.

Figure 2 A sketch map to illustrate different samples in the fracture network.

Results

The correlation analysis between the 1D & 2D intensity parameters and the 3D ones is summarized in **Table 2**. Sample orientations influence the correlations, and random sample orientations yield the

Table 2: Correlations between 1D & 2D intensity parameters and 3D intensity parameters

Correlation Coefficient	I_{2D}	P_{21}	P_{20}	P_{10}	Sample direction	Case
I_{3D}	0.89	0.91	0.97	0.77	σ_1	1
P_{32}	0.88	0.98	0.87	0.64	σ_1	1
P_{30}	0.79	0.79	0.98	0.76	σ_1	1
I_{3D}	0.95	0.93	0.97	0.52	σ_2	2
P_{32}	0.99	1.00	0.88	0.47	σ_2	2
P_{30}	0.84	0.81	0.97	0.47	σ_2	2
I_{3D}	0.92	0.94	0.98	0.70	σ_3	3
P_{32}	0.89	0.99	0.87	0.62	σ_3	3
P_{30}	0.82	0.84	0.99	0.65	σ_3	3
I_{3D}	0.72	0.34	0.89	0.37	Random	4
P_{32}	0.65	0.28	0.81	0.29	Random	4
P_{30}	0.67	0.34	0.87	0.36	Random	4

Figure 3 Variation of correlation coefficients with the numbers of samples to be averaged in the three cases (From left to right: Cases 1, 2 and 3).

poorest correlations between the lower and higher dimensionality intensity parameters. For the sample orientations parallel to principal stresses, P_{10} doesn't correlate with any of the 3D intensity parameters, especially P_{32} . If samples are taken in the direction parallel to σ_2 , the correlations are even worse. The 2D parameters, I_{2D} , P_{21} and P_{20} , all have good correlations with I_{3D} and P_{32} . P_{30} has a stronger correlation with P_{20} , rather than with I_{2D} and P_{21} .

The results in **Table 2** are averages of 100 samples. In practice, however, it is impossible to acquire enough samples for a meaningful correlation analysis. To investigate the minimum number of samples required for a good and stable correlation, we choose several pairs of parameters that have correlation coefficients larger than 0.9. We also include P_{32} and P_{10} , since this pair of parameters has been extensively studied by other researchers. The results of Case 1 - 3 are shown in **Fig. 3**. For all three cases, we find that the minimum number of samples required to have a good and robust correlation is about 20. The correlations between small cube samples and original fracture networks are shown in **Fig. 4**. I_{3D}

Figure 4 Variation of correlation coefficients with sizes of cube samples.

correlates well with all three 3D intensity parameters, I_{3Ds} , P_{32s} and P_{30s} . P_{32} correlates with P_{32s} and

P_{30s} . P_{30} correlates well only with I_{3Ds} . When the size of the cube sample is larger than 10 percent of the system size, the correlation coefficients are larger than 0.8, which means that the samples capture most of the information about the underlying network.

We also investigate the minimum number of samples required to have a good and stable correlation. We choose three pairs of parameters as examples to find this minimum number. These pairs are I_{3D} and P_{30s} (Case 1), P_{32} and P_{32s} (Case 2), and P_{30} and P_{30s} (Case 3). The results are shown in **Fig. 5**. To achieve the correlation coefficient larger than 0.8, the cube samples sizes must be 10 percent of the original system size, and the minimum number of samples about 60.

Figure 5 Variation of correlation coefficients for different sizes and numbers of the cube samples to be averaged (From left to right: I_{3D} vs P_{30s} , P_{32} vs P_{32s} , P_{30} vs P_{30s}).

Conclusions

- Fracture sampling orientation impacts correlations between the 2D and 3D parameters. Samples parallel to the principal stresses yield better correlations.
- The 3D intensity parameters, I_{3D} , P_{32} and P_{30} , can be predicted from one or more 2D intensity parameters, e.g., I_{2D} , P_{21} or P_{20} . The minimum number of samples required for a good correlation is about 20.
- The 1D logging measure, P_{10} , doesn't have a good correlation with the 3D intensity parameters, especially for the samples parallel to the intermediate principal stress σ_2 .
- 3D intensity parameters can be predicted from one or more 3D intensity parameters of small cube samples. However, the cube sample sizes should be larger than 10 percent of the underlying fracture network, and the minimum number of cube samples should be larger than 60.

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