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Finally, an objective way to infer JRC from digitized fracture traces

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ABSTRACT: The understanding of hard rock fractures is important for topics such as geomechanics, rock mechanics and ground water flow and transport. One key aspect is the geometry of the two surfaces defining a fracture, often referred to as roughness. Probably the most used measure to determine the roughness is the Joint Roughness Coefficient, JRC. The accurate way to determine JRC is to do shear tests and back calculate JRC. However, most often this procedure is neither feasible nor possible. Instead, JRC is commonly determined by a subjective comparison of the fracture and some type traces. It has been shown that at least 50 geologists are needed to get stable inferences of JRC. Lately, a model has been developed that is supposed to objectively infer JRC from the two fractal parameters H and $\sigma\delta h$(1 mm). This model is used to predict JRC of nine synthetic traces. The results are compared to the visually interpreted JRC values by eleven geologists. The differences between the JRC, by the model, and the median value of the geologist are negligible. Hence, the model is an objective way to infer JRC from digitized fracture traces.

1. INTRODUCTION

The understanding of hard rock fractures is important for topics such as geomechanics, rock mechanics and ground water flow and transport. One key aspect is the geometry of the two surfaces defining the fracture, often referred to as the roughness of the fracture. The roughness, together with strength and deformability of the surrounding rock, control the mechanical behavior of the fracture by the appearance of contact points, whilst the flow and solute transport are controlled by the voids between the contacts. Hence, it is important to have an accurate description of the fracture roughness for many applications in geoscience.

One commonly used method to infer JRC of a fracture trace is to compare it with different type curves, such as the ten classic traces in Barton and Choubey, 1977. This subjective visual comparison, often performed by a single geologist, may have a large, un-quantified, uncertainty. Another problem of the visual inspection is that the size of the sample and the type trace may be different, resulting in large uncertainty in the inferred JRC due to scaling.

A model that is supposed to predict JRC using the objective measures of fractal dimension and asperity distribution has been developed by Stigsson and Mas Ivars, 2018. They have shown that their model fulfills the minimum requirement that it can reproduce the data underlying the development of the model, i.e. the ten type traces in Barton and Choubey, 1977. However, how well the model can predict JRC from arbitrary traces has not yet been investigated.

Hence, in this study nine synthetic traces are used to objectively calculate JRC and compare it to the median and quartiles of subjectively inferred JRC from an ensemble of eleven geologists.

2. THE MODEL

The most common way, so far, to accurately determine JRC is to do tilt tests and back calculate JRC of the fracture at hand. However, most often this procedure is neither feasible nor possible. Instead, JRC is often subjectively inferred from some type curves. Beer et al., 2002, investigated the mean and variance in inferred JRC values by letting multiple geologists, >120, infer JRC for 3 traces using an online survey. One result of the study was that about 50 geologists were needed to obtain a stable mean and variance of the interpreted traces. This indicates that it is wise to use several geologists to get a reliable estimate of JRC, which is most often not the case.

In the literature there are numerous examples (from Turk et al., 1987, to Li and Huang, 2015, via e.g. Lee et al., 1990, Wakabayashi and Fukushige, 1992, Xie and Wang, 1999, Jiang et al., 2006, Bae et al., 2011, etc,), where the fracture traces have been evaluated using methods not applicable to fracture traces, such as the divider method, compass walking, or h-l method (Stigsson and Mas Ivars, 2018). Results from such studies are therefore highly questionable. Other studies (e.g. Tse and Cruden, 1979, Yang et al., 2001, Tatone and Grasselli, 2010) have only used different types of asperity measures to develop models to predict JRC. However, to be able to capture both the small scale and large scale behavior of fractures simultaneously both the fractal dimension and asperity distribution have to be regarded.

Stigsson and Mas Ivars, 2018, assume that fractures are mono-fractal self-affine surfaces (Mandelbrot, 1985, Russ, 1994, Renard et al., 2006, Candela et al., 2009, Brodsky et al., 2011, Candela et al., 2012) and, hence, use both the fractal dimension and an asperity measure to infer JRC.

As the measure for fractal dimension Stigsson and Mas Ivars, 2018, use the Hurst, or Hausdorff, exponent, H. The relationship between H and the fractal dimension of a fracture trace, D_{1D} is:

$$H = 2 - D_{1D} \tag{1}$$

For the asperity measure Stigsson and Mas Ivars, 2018, use the standard deviation of height differences of points Δx apart, $\sigma\delta h(\Delta x)$. The measure is, hence, dependent on Δx and scales as

$$\sigma\delta h(\Delta x) = c \cdot \Delta x^{H} \tag{2}$$

Where c is the standard deviation of height differences when $\Delta x = 1$, and H is the Hurst exponent.

The model in Stigsson and Mas Ivars, 2018, was developed by evaluating the classic ten type traces in Barton and Choubey, 1977. The traces were digitized twice by the authors themselves and as a complement an algorithm based digitalisation made by Jang et al., 2014, was used.

To get as accurate and robust inferences as possible Stigsson and Mas Ivars, 2018, used 4 different evaluation methods applicable to mono-fractal self-affine traces; Power Spectrum using Fast Fourier Transform; Standard Deviation of the Correlation Function; Korcak plot of Zero Sets; and Box Counting. Each method has a unique bias and uncertainty, and by combining the results from several methods the uncertainty can be reduced.

Stigsson and Mas Ivars, 2018, recognized that the resolution of the traces in Barton and Choubey, 1977, is low and hence the inference of fractal parameters uncertain. Therefore Stigsson and Mas Ivars, 2018, chose to develop a basic multi linear model without any interaction between parameters. Hence, the inferred fractal parameters together with the back calculated JRC values were used to run a MLR, multiple linear regression, analysis of the data, to develop the model.

The outcome was a model that predicts JRC from H and $\sigma\delta h(1mm)$ where all three coefficients in the equation were significant to highly significant ($6 \cdot 10^{-6} < p < 0.04$). The model was statistically tested and it was concluded that:

- The F-test, i.e. the null-hypothesis of an intercept only model working as good as the developed, could be rejected on $p = 3 \cdot 10^{-6}$.
- The Jarque-Bera test, i.e. the null-hypothesis of errors being normally distributed, could not be rejected $p = 0.8605$.
- The Breusch-Pagan test and Koenker-Bassett test, i.e. the null-hypothesis of homoscedasticity, could not be rejected $p = 0.6036$, and $p = 0.5612$ respectively.
- The model has an adjusted R^2-value of 0.9651, i.e. the model can explain 96.5% of the variance of JRC.

Using this model to estimate the JRC of the ten type traces in Barton and Choubey, 1977, the mean error is zero and the standard deviation one unit. As a comparison, the standard deviation of interpreted JRC values, from the >120 geologists participating in the study of Beer et al., 2002, was 2.5-3 units. However, using the interpretations from the self-judged group of “Very experienced at JRC estimation” in Beer et al., 2002, the standard deviation decreased to about 1.5 Units.

3. METHOD

To accurately reproduce the data that are underlying the development of a model is an absolute minimum request of the model. However, how well the model can predict other data is of great interest.

In lack of a collection of fractures to scan and perform shear or tilt tests a simpler approach is used. An ensemble of nine synthetic fracture traces is generated with known H and $\sigma\delta h(1mm)$. The JRC of these traces are evaluated using the model and compared to the visual interpretation of JRC done by a group of skilled geologists. It is recognised by the author that the approach does not show how well the model can predict JRC, but how well it can predict the subjectively interpreted JRC by an ensemble of geologists.

The generation of the traces was set up to theoretically produce nine traces between the JRC-values 2 to 18 in steps of 2 units. Another desire was to spread the generated Hurst exponent, and, hence H was varied between 0.5 and 0.9 in steps of 0.05. The desired JRC and H were randomly chosen to avoid any correlation between the parameters that could affect the results. This set up resulted in $\sigma\delta h(1mm)$ between 0.05 and 0.36 mm.

There are different causes why there may be differences between the fractal parameters used as input and the inferred values of the very same parameters. For the first, the generation method of fracture traces includes stochastic processes; Secondly, traces might locally have different statistics and hence a sub-trace being affected; and to the last; the number of vertices on the trace will affect the variance of the evaluated parameters. To minimize the bias and uncertainty the same 4 methods used in Stigsson and Mas Ivars, 2018, are used to evaluate the traces. The theoretical JRC and the predicted JRC from evaluating the traces are shown in table 1.

Table 1. The difference between desired (Theoretical), and predicted (Inferred) JRC

Trace #	Theoretical JRC	Inferred JRC
1	12	10.7
2	2	2.1
3	4	2.6
4	16	16.5
5	8	7.7
6	18	17.9
7	10	11.7
8	14	14.1
9	6	6.4

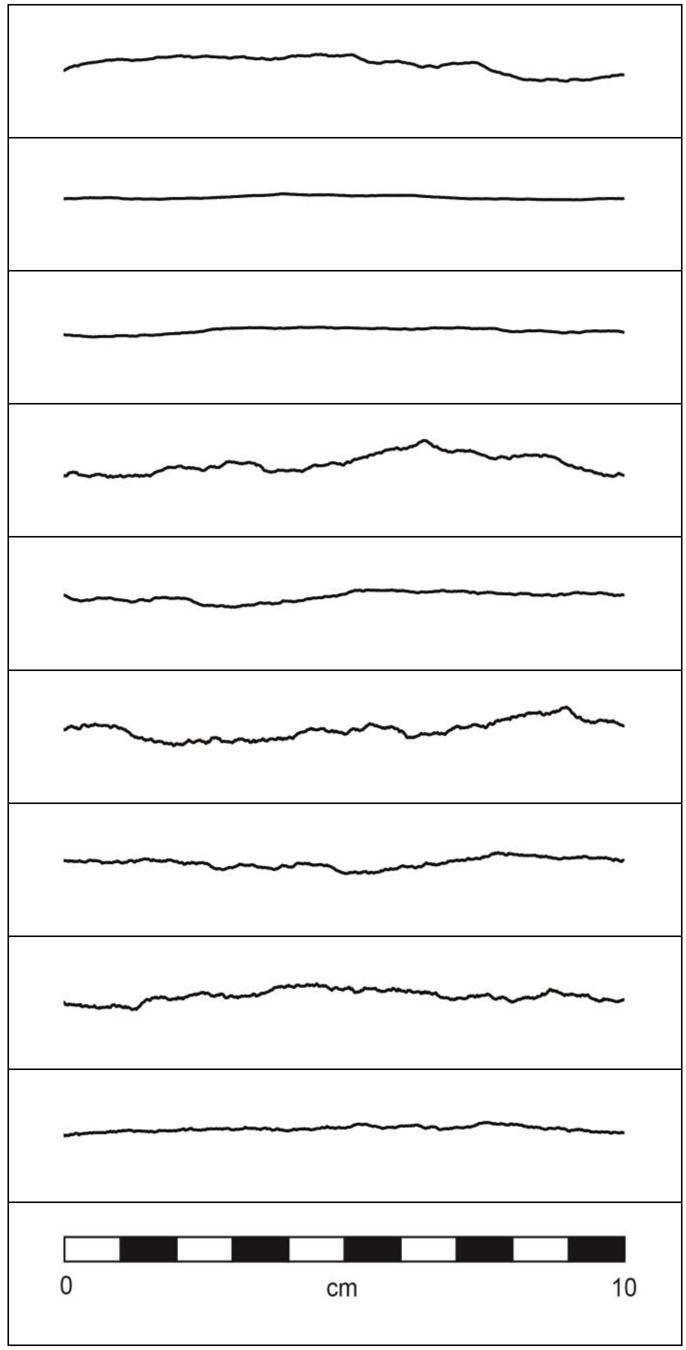

Fig 1. The nine traces sent to the community of geologists.

The nine traces, Fig 1, were sent by e-mail to the community of geologist encouraging them to forward to other colleagues in the field. Eleven geologists obeyed the call and sent back their judgement of JRC.

The geologists could chose to fill in one single JRC value or a span for each of the nine traces. If a range was chosen the mean was used in the evaluation phase. The geologist also had the possibility to mark if they thought that a trace looked odd. Only one of the geologists used this possibility, but still inferred a JRC value for the trace.

There was no possibility for the geologists to indicate their level of experience evaluating JRC from fracture traces and hence, all results are valued equal. This despite it was recognised that some geologists were closer to the theoretical value than other. For some geologist the estimates were very close for all but one or two traces.

4. RESULTS

There were eleven geologists answering the call for estimating JRC from the nine synthetic traces. This is, unfortunately, too few estimators to get stable statistics (Beer et al., 2002).

To get an idea of the uncertainty of the estimates provided by the geologists the cumulative mean and cumulative standard deviation as a function of the order of incoming result were plotted. As shown in Fig 2 the mean is quite stable for the low values of JRC, whilst there are still some trends in the JRC estimates for the higher values, though small. The standard deviations, however, are not stable showing a clear decreasing trend from four to seven interpreting geologists and onward, except for the smoothest trace that are stable already from about four interpretations, Fig 2.

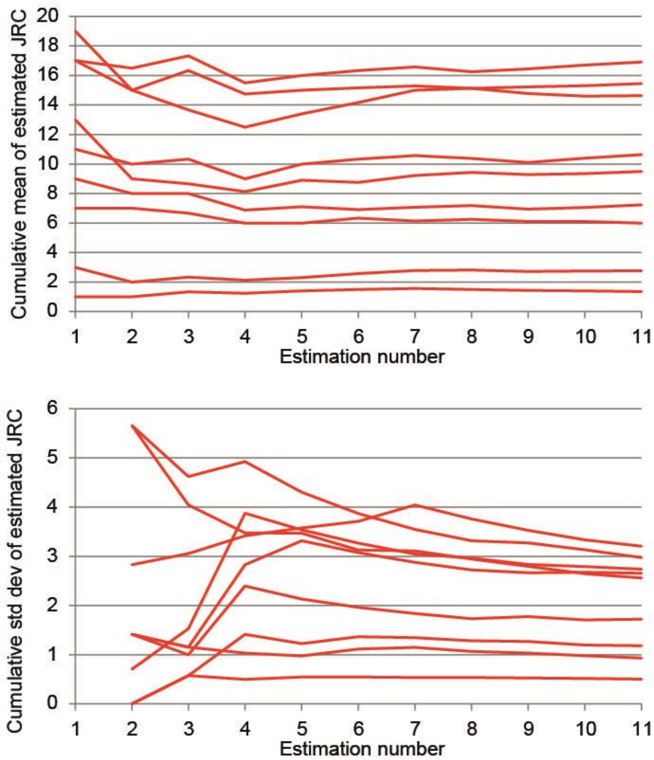

Fig. 2. The development of mean (upper graph) and standard deviation (lower graph) of the estimated JRC of the nine synthetic traces.

The low number of interpreting geologists makes it doubtful for interpretation by mean and standard deviation, tough the spreads of values for each trace have a tendency to be normally distributed. Instead the data are described using median and quartiles and visualized as boxplots, Fig 3.

The thick horizontal blue line represents the median of the interpreted values and the upper and lower quartiles are shown by the box. The whiskers show the value inside 1.5 IQR (Inter Quartile Range). Seven of the 99 interpretations fall outside the lower 1.5 IQR, and are marked as open circles. None of the interpretations fall outside the upper 1.5 IQR, hence, the upper whisker in Fig 3 shows the maximum interpreted value for each trace.

The maximum differences in interpreted JRC values are quite large. For five of the nine traces the spread is eight units or above, with an extreme value of eleven units for the traces with predicted JRC 16.5.

The red 1:1 slope in Fig 3 is added as guidance for the eye when visually evaluating the data. If the 1:1 line crosses the median, blue thick line, at the center there is a perfect match between interpreted median and predicted JRC. The difference between the interpreted median and predicted JRC is between -1.07 and +0.87 with an average difference of -0.19, i.e. the model slightly under-predicts the interpretation of the geologists, Table 2. However, the IQR of the interpreted JRC's are much larger and, hence, the small difference is not significant.

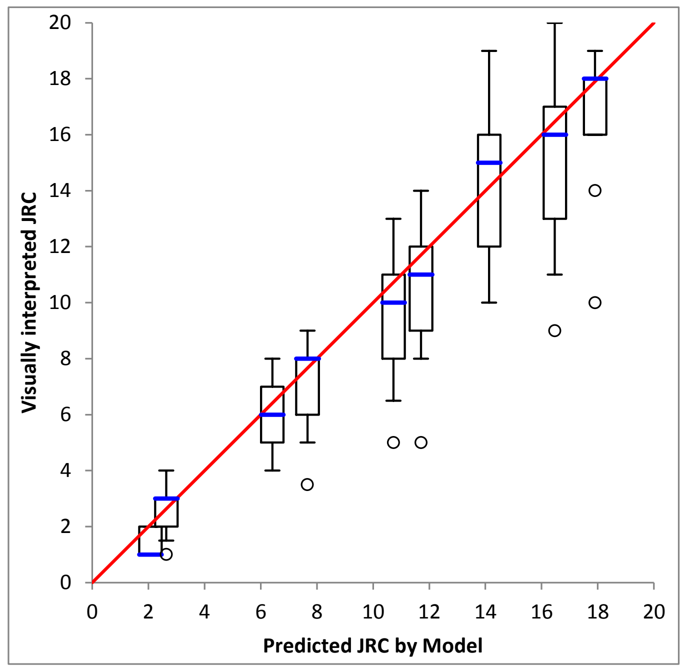

Fig. 3. The visually interpreted JRC values by the eleven geologists as box and whiskers as a function of the predicted JRC by the model. The red 1:1 slope is added as guidance for the eye.

Table 2. The difference between predicted JRC by the model and interpreted median JRC by the geologists

Trace #	Predicted JRC	Interpreted JRC	diff
1	10.7	10	-0.73
2	2.1	1	-1.07
3	2.6	3	0.36
4	16.5	16	-0.47
5	7.7	8	0.34
6	17.9	18	0.10
7	11.7	11	-0.71
8	14.1	15	0.87
9	6.4	6	-0.41

During the evaluation of the results it is noted that one geologist is responsible for four of the seven outliers and that the very same geologist has interpreted six of the ten largest deviations from the predicted JRC. To investigate how sensitive the results are to this single geologist the data are re-analyzed excluding this geologist´s results.

The median is not sensitive to extreme values themselves, but only the contribution to be above or below the median. Hence, the effect on the median will be minor since there are relatively many values close to the median, Fig 4. However, due to the few data, excluding one entry will affect the IQR-limits to some extent; mostly decrease it. This will result in more values being regarded as outliers, i.e. outside the 1.5 IQR. Despite excluding the extreme entries there will still be 3 traces where the maximum spread in interpreted JRC will be eight or larger.

The results from the sensitivity study is what can be expected from looking at Fig 2; The median values start to be stable whilst the standard deviation values still have some trends.

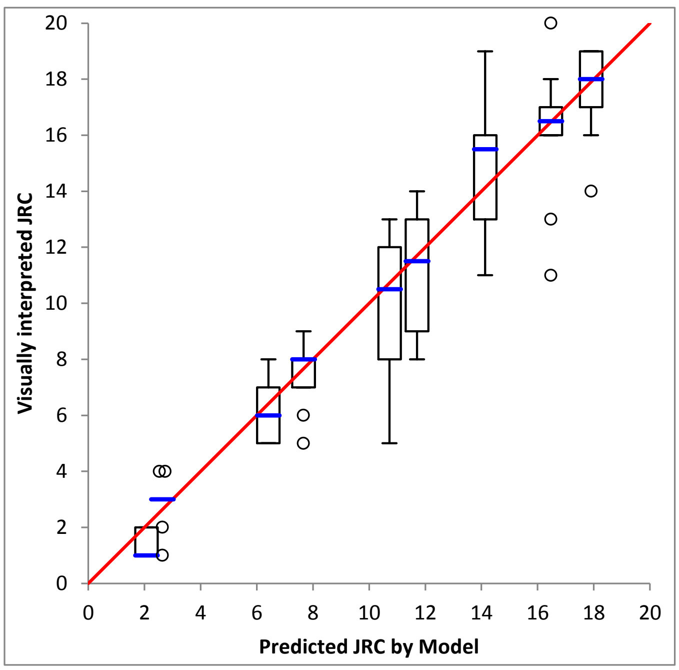

Fig. 4. Box and whisker plot of visually interpreted JRC values by all but one geologist.

5. DISCUSSION

This small study shows that more than eleven geologist are needed to get stable statistics when interpreting JRC from digitized traces. This is in accordance with the findings in Beer et al., 2002, where it was concluded that about 50 geologists were needed to get stable statistical measures such as mean and standard deviation.

Despite only eleven geologists interpreting the traces in this study the median was almost insensitive to excluding results from the geologist having the most extreme values. The IQR was, however, affected to some extent by the exclusion of these nine data.

The maximum spread in visually interpreted JRC for a single trace is large, ≥ 8, for five traces. Excluding the extreme data set there will still be three traces with maximum difference ≥ 8. Hence, most of the visual interpretations from a single geologist may largely deviate from the expected JRC, as well as the interpretation of a single trace may largely deviate from expected JRC despite all other interpretations being close to the expected.

These results show clearly that visual interpretation from a single geologist may be specious and an objective approach is preferable. One such approach may be the model developed by Stigsson and Mas Ivars, 2018, where the two fractal parameters H and $\sigma\delta h(1\text{ mm})$ are used to infer JRC.

The model by Stigsson and Mas Ivars relies on an accurate inference of the two fractal parameters describing a mono-fractal self-affine surface. The inference of the fractal parameters is also objective, i.e. it relies on prescribed algorithms. Using several methods the uncertainty in the inferred parameters may be decreased.

However, it is important to notice that this study does not confirm whether the model by Stigsson and Mas Ivars, 2018, can predict the correct JRC or not. It only shows that the model is as good as an ensemble of geologists visually interpreting the traces. The model may, hence, be further developed. A suggested improvement would be to carry out numerical shear tests on synthetic fractures generated using Monte Carlo realizations. The numerical models should be constrained by shear tests on real fractures that have been scanned using high resolution equipment. Such study would give the possibility to constrain or refine the model developed by Stigsson and Mas Ivars, 2018.

6. CONCLUSON

This study shows that the model, developed by Stigsson and Mas Ivars, 2018, is equally good at inferring JRC values based on the fractal dimension and an asperity measure from fracture traces as an ensemble of eleven geologists visually interpreting the traces. Hence, the model is an objective way to infer JRC from digitized fracture traces.

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