The influence of spatial resolution and noise on fracture network properties calculated from X-ray microtomography data

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Abstract

Rock deformation experiments performed at X-ray synchrotrons provide unique insights into the nature of fracture network development. However, these insights depend on the limitations of the X-ray tomography data. Here, we examine how spatial resolution and noise influence the calculated fracture network properties. To assess the influence of spatial resolution, we acquire two overlapping X-ray tomograms with spatial resolution that differ by an order of magnitude. To assess the influence of noise, we produce sets of synthetic tomograms with varying degrees of noise, including point-source noise and blurring noise. In the absence of noise, the differing spatial resolutions produce calculated porosities that differ by 0.05%, or 30% of the porosity measured in the high-resolution data. The fracture property that changes the most in the datasets of varying resolution is the fracture surface area, rather than the volume, length, or aperture. The two types of noise influence the porosity and fracture characteristics in opposite ways. In the synthetic tomograms in which higher values indicate fractures, added point noise increases the porosity while blurring noise decreases the porosity. In volumes with a mapping of gray values in which fractures have lower values, this trend would be reversed. This study is the first to quantify differences in fracture network properties extracted from X-ray tomograms due to spatial resolution and noise.

Keywords
X-ray tomography; segmentation, fractures; rock deformation; spatial resolution

Highlights

- We assess the influence of spatial resolution and noise on fracture properties.
- Porosity differs by 0.05% between the tomograms of two spatial resolutions.
- Varying the spatial resolution produces the largest changes in the surface area.

- The calculated fracture volume, lengths and apertures change the least.
- Point noise increases the porosity; blurring decreases the porosity.

1. Introduction

The field of digital rock physics uses precise measurements of rocks to construct three-dimensional numerical representations of the system. Analysists then use these numerical representations to calculate various properties of the rock that are difficult to measure on natural rock samples, such as the elastic moduli, electrical resistivity, permeability and porosity [e.g., 1, 2, 3]. These numerical representations also enable analysists to perform simulations on these digital rocks, such as triaxial compression and fluid flow tests, that would be more expensive to perform on real rocks. The fundamental steps that comprise a digital rock physics investigation include 1) capturing detailed images of the rock, ideally in three-dimensions, 2) classifying or segmenting the rock microstructure into different mineral phases and/or different solid and fluid phases, 3) building a numerical representation from the segmented image of the rock, and 4) performing the desired numerical simulations. To accomplish step one, experimentalists may capture the highest spatial resolution three-dimensional images at X-ray synchrotron sources [e.g., 4, 5, 6]. Desktop X-ray sources can also provide lower resolution images.

In addition [JM1]to the insights provided by digital rock physics analyses, imaging during in situ synchrotron X-ray microtomography experiments reveals detailed mechanisms of rock deformation leading to system-size failure [e.g., 7, 8]. In these experiments, a powerful synchrotron X-ray source is coupled with an X-ray transparent deformation apparatus to acquire three-dimensional images of rocks while they are at the stress and/or temperature conditions of the natural crust [e.g., 9, 10, 11]. These experiments thus allow analysists to capture the evolving fracture network of the rock at a range of stress and temperature states, such as the evolving stress field that may precede a large earthquake.

This ability to observe rock deformation in situ during triaxial compression significantly increases the temporal resolution of the observations of these types of experiments. This non-destructive technique also reduces the uncertainty in the observations caused by unloading at the end of the experiment. Consequently, these in situ observations have provided fundamental insights into a wide range of geophysical phenomena, including the potential precursors that signal the timing of catastrophic failure, such as earthquakes [e.g., 12, 13, 14], the evolution of the fracture network during deformation [e.g., 15, 16, 17], the evolution of the local strain field [18, 19, 20, 21], the similarity between rock failure and critical phase transitions [e.g., 8, 22, 23], the influence of heating on shale [e.g., 24, 25, 26, 27], the deformation of shale during indentation [28], the deformation of porous rocks and sediments [e.g., 29, 30], the fragmentation of chondrites [31], hydration reactions that break rock during metamorphism [32, 33, 34], porosity reduction by pressure solution creep [35], the flow of melt in volcanic rocks [36], and the partitioning of the energy budget [37]. Because this technology has provided such significant insights, it is critical to examine the shortcomings in the methodologies and how they may be improved.

A common caveat of this technique is the spatial sampling and the corresponding spatial resolution [e.g., 38, 39, 40, 41[JM2]]. The spatial sampling is the side length of a pixel in two-dimensional images and a voxel in three-dimensional volumes. The spatial resolution, in contrast, measures the ability to separate two different objects. Thus, following the Nyquist-Shannon sampling theorem [42], the spatial resolution is at least twice the sampling distance (i.e., the Nyquist frequency). In a three-dimensional volume acquired at a synchrotron, the spatial resolution is a function of the voxel size and blurring produced during tomogram acquisition and reconstruction. The spatial resolution thus influences the proportion of the true fracture network that we may identify in the tomogram. To extract the fracture network, we must decide which voxels are those dominated by solid and which are dominated by air or pore fluid. This classification step is often called segmentation. Thus, it is challenging to identify fractures with thicknesses (apertures) that are less than twice the spatial sampling [e.g., 43]. This lack of identification of the smallest fractures leads to intuitions about the difference between the true fracture network and the observed fracture network. For example, we expect that the true porosity is higher than the observed porosity. Because many of the fundamental insights about rock deformation and rock properties depend on the characteristics of the porosity and fracture network properties calculated from segmented tomograms, it is critical to more precisely quantify the differences between the true and calculated fracture network.

In addition to the spatial resolution, the accuracy of the segmentation depends on the noise level, and spatial complexity of the material [e.g., 1, 2, 6, 44, 45[JM3]]. Unless experimentalists measure a property independently, such as the porosity, we cannot know the difference between the true value of the property and the value measured from a tomogram. Thus, we usually cannot determine the accuracy of the measurement, unless we use synthetic datasets with a known ground-truth dataset [e.g., 46, 47]. A previous analysis [47] demonstrated that three segmentation techniques (global thresholding, watershed, machine learning) provide different results depending on the noise of the image. When the noise level is low in X-ray tomography data, the difference between the three segmentation techniques is negligible [Figure 3h in 47]. Thus, to assess the influence of spatial resolution and noise, in this analysis we compare the fracture network properties calculated from two tomograms of differing spatial resolutions and various degrees of noise.

2. Methods

2.1. Analysis design[JM4]

We compare the fracture characteristics calculated from two tomograms that differ in spatial resolution by one order of magnitude (**Figure** 1). Typically, in experiments at the tomography beamline ID19 at the European Synchrotron and Radiation Facility (ESRF), we only acquire tomograms with a spatial sampling of 6.5 µm/voxel side length. To compare the influence of resolution, in one experiment we also acquire one tomogram at a higher spatial sampling of 0.65 µm/voxel side length (**Figure** 1). We acquire tomograms with the lower resolution, rather than the higher resolution, because it allows capturing the entire core sample within a volume (cube) of 1 cm^3. In contrast, the higher resolution image is restricted to a volume of 1 mm^3. The higher resolution tomogram thus only overlaps a small volume of the lower resolution tomogram. This unique dataset allows precisely comparing the differences in fracture network characteristics due to differences in spatial resolution.

To compare these differences, we extract fracture networks from the portion of the low-resolution data that overlaps the high-resolution data (**Figure** 1), and calculate properties of the fracture network, such as the porosity and geometric characteristics of individual fractures. Because some fractures may have apertures, or portions of their aperture, below the spatial resolution, the calculated fracture properties must be inaccurate. The key questions we examine here are the magnitude of the inaccuracy of the calculated characteristics, and which characteristics suffer the most from the limited spatial resolution. For example, the fractures in the high-resolution data appear more continuous and thicker than the fractures in the low-resolution data (**Figure** 2). To quantify how the limited spatial resolution influences the calculated porosity and other fracture characteristics, such as the volume, surface area, length, and aperture, we compare the fracture characteristics calculated using the tomograms at the two resolutions.

Another key caveat of the data acquired in X-ray tomography experiments is the noise included in the tomogram during acquisition. To quantify the influence of noise on the calculated fracture characteristics, we produce synthetic tomograms from the low-resolution tomograms with two types of noise. Then, we calculate the same suite of aforementioned fracture characteristics. We add point-source noise in order to mimic the effects of X-ray scattering to one set of synthetic tomograms. We also add blurring noise to another set of synthetic tomograms in order to mimic the effects of inadequate focusing of the beamline optics. Comparing the resulting fracture characteristics quantifies how both the resolution and noise change the calculated characteristics, and thus how inaccurate these calculations may be in a tomogram subjected to varying degrees of noise. Here, we assume that the fracture properties calculated with the high-resolution data that lack noise are closer to the true values of these properties than the low-resolution data. By quantifying these differences in the calculated fracture properties, we help constrain the true inaccuracy of the calculated fracture properties, and thus how these inaccuracies may bias analyses of the evolving fracture network and pore structure.

In the present analysis, we extract the fracture networks using one segmentation method based on a global threshold that we have used in previous analyses [e.g., 15]. Although we have used this method in previous studies, we have not described the algorithm in precise detail that would allow replication. Here, we describe the details of this algorithm so that other scientists may apply it to their data, and provide the corresponding code. In future work, we assess the influence of the segmentation method on the calculated fracture properties.

2.2. Experimental conditions

To quantify the influence of spatial resolution on the observed fracture network, we acquired two tomograms of two spatial resolutions that overlap the same volume of rock (**Figure** 1, **Figure** 2). We acquired these tomograms during a triaxial compression experiment on Westerly granite. During this experiment, we inserted a 1 cm tall and 0.4 cm wide cylinder of Westerly granite into the HADES apparatus [9]. This apparatus enables acquiring tomograms of the deforming rock while it experiences triaxial compression loading inside the rig at the temperature and pressure conditions relevant for crustal processes. In this experiment, we applied a confining stress (10 MPa) and then increased the axial stress in steps. After each axial stress increase, we acquired a tomogram at the typical (lower) resolution of 6.5 µm/voxel. When the rock was subjected to an axial stress of 149.5 MPa (and differential stress of 139.5 MPa), we also acquired the higher resolution tomogram at 0.65 µm/voxel. [JM5]To acquire this second tomogram, we changed the resolution by changing the objective in front of the camera from x1 to x10, while keeping all the other equipment at the beamline the same, including the distance between the sample and the camera (36 cm). The experiment was performed at ambient temperature.

Each X-ray tomography acquisition lasts for 1.5 minutes. When using the full white beam of the synchrotron, with maximum energy close to 200 keV, the average beam energy crossing the sample is close to 85 keV because the triaxial rig absorbs a proportion of the X-ray energy. For the low-resolution volume, we acquired 1600 radiographs, at 32 bytes gray scale resolution of X-ray absorption, while the sample was rotated over 180°. The volume of the reconstructed sample contains 1600 x 1600 x 1600 voxels. For the high-resolution volume, we acquired 2500 radiographs. The volume of the reconstructed sample is 2048 x 2048 x 2048 voxels. Both volumes are available publicly [48]. In order to analyze the same volume of the rock, we cropped the lower resolution tomogram so that it only overlaps the higher resolution tomogram.[JM6]

2.3. Data reconstruction and spatial resolution

From the X-ray radiographs, we reconstructed three-dimensional volumes using both X-ray absorption and phase contrast [49]. We use the phase contrast data to build the synthetic tomograms in this analysis because the X-ray absorption data was noisier than the phase contrast data. During the reconstruction, we applied corrections to remove acquisition noise, including ring artefacts, and to smooth variations of intensity of the X-ray source during the experiment. To remove noise from the reconstructed images, we pre-processed these data using the commercial image analysis software AvizoFire™. First, we denoised the volumes using a non-local-means filter [50]. Second, we cropped the low- and high-resolution data so that these datasets exactly overlap each other, thereby aiding direct comparison of their subsequent segmentations.

On beamline ID19, we performed a test to determine the spatial resolution. We used a standard pattern of Siemens stars and line pairs to separate objects. This test showed that we could separate objects of the size of the voxel. Due to phase contrast, we can also detect features that are smaller than the voxel size. For example, we can observe some cracks in the phase contrast data, but not the absorption fields because the crack interfaces produce contrast. On beamline ID17 at ESRF, using the same detector and optics as on beamline ID19, [51] found a spatial resolution of the order of 20 micrometers when the voxel size was 6.5 micrometers (Table 5 of [51]). However, these authors did not use the phase contrast imaging technique we used on beamline ID19. Moreover, they used an energy (50 keV) lower than the energy used here (85 keV). In summary, the phase contrast enables differentiating between objects with dimensions near the voxel size. If the direct measurements of [51] apply to our data, then our low-resolution tomogram with a spatial sampling distance of 6.5 micrometers has a true spatial resolution of about 20 micrometers. For the high-resolution tomogram, with a spatial sampling distance of 0.65 micrometers, the true spatial resolution is about 2 micrometers.[JM7]

2.4. Extraction of the fracture network

Following tomogram reconstruction and denoising, we extract the fracture network from the surrounding solid rock core. The tomograms consist of a three-dimensional field of scaled values derived from the linear attenuation coefficient, which depends on the X-ray energy and density of the material. These values are often called the gray values of the tomogram. To extract the fracture network, we identify a global threshold of the gray values that represents the boundary between the solid and fluid. We chose this segmentation method because it is well-established, contains only one parameter required to segment the data (the gray scale threshold) and segments tomograms with little computational cost.

To select this global threshold, we follow the idea that the two populations of the voxels dominated by solid and those dominated by air form Gaussian distributions (**Figure** 3). Experimental observations support this idea because the main minerals in Westerly granite are quartz and feldspar, which have similar X-ray absorption properties. In addition, denser phases (biotite) have an absorption signature outside of the range of quartz and feldspar, and thus may be independently segmented**.** Thus, the histogram of gray values of a given tomogram that encompass the air, quartz, and feldspar should consist of two overlapping Gaussian distributions. The global threshold between the solid and air thus represents the boundary between these two Gaussian distributions. Thus, identifying this threshold requires finding an equation of two overlapping Gaussian distributions that best fits the histogram of gray values.

To find this equation, we calculate a histogram (or probability distribution function, PDF) of the gray values in semi-log space that includes the range that contains the pores, quartz and feldspar gray values (**Figure** 3). We formulate the PDF, and corresponding Gaussian equations, in semi-log space because 1-2% of the tomogram is air-dominated voxels, while 98-99% is solid-dominated. Then, we fit two overlapping Gaussian distributions to the $\log_{10}$(PDF) of the tomogram gray values (**Figure** 3a). Fitting these distributions requires finding the three different fitting parameters of both Gaussians. A Gaussian function, $g(x)$, includes the real constants *a*, *b*, and *c*:

$$g(x) = aexp\left(\frac{-(x-b)^2}{2c^2}\right). \qquad \text{Eq. 1}$$

Thus, we must find the parameters *a*, *b*, and *c* of both Gaussian distributions, with a total of six free parameters to identify the function *f(x)* that describes the two overlapping Gaussian distributions in log space:

$$f(x) = log_{10}\left(aexp\left(\frac{-(x-b)^2}{2c^2}\right) + dexp\left(\frac{-(x-e)^2}{2f^2}\right)\right) \qquad \text{Eq. 2}$$

where the parameters *d, e*, and *f* in Eq. 2, represent the values *a*, *b*, and *c*, in Eq. 1 for the second Gaussian population. To perform the fit of the PDF of the gray values, we select the minimum and maximum gray values to which the two Gaussian distributions will be fit. These values may be different from the minimum and maximum values of the full populations because sometimes the PDF of the gray values contains an additional peak when there are distinct populations of mineral density. Thus, the total PDF will contain three peaks and fitting two Gaussian distributions will not be successful.

Next, we calculate the six free parameters that best fit $f(x)$ to our data using a standard non-linear fitting procedure with a least-square minimization criterion. Then, we identify a boundary between the two populations that represent the solid- and air-dominated voxels. To identify this boundary, we calculate the second derivative of the fit, $f(x)$, and then find where the second derivative is closest to zero, indicative of the inflection point between the two Gaussian distributions (**Figure** 3b). This method then uses this gray value as the global threshold, t_G, between the solid- and air-dominated voxels. The solid-dominated voxels are those with gray values above t_G, and the air-dominated voxels are those with gray values below t_G. Note, the low-resolution and high-resolution data have different t_G.

3. Results

Here, we first examine how varying the spatial resolution of the tomogram changes the calculated fracture characteristics. We also assess how changing the global segmentation threshold changes the calculated characteristics. We then test how varying the types and magnitudes of noise influence the calculated characteristics.

3.1. How spatial resolution influences the characteristics of the fracture network

The example two-dimensional slices of the segmented fracture network appear to differ in the low-resolution and high-resolution data (**Figure** 3d-g). To quantify these differences using the fracture characteristics, we must identify the individual fractures within the segmented three-dimensional image. We extract the fractures from the tomogram using the global threshold identified with the method described in Section 3.2: voxels with gray values above and below the derived threshold are segmented into solid and fracture-dominated voxels, respectively. Thus, the segmented volume is a binary field of zeros and ones with ones representing the voxels dominated by air (i.e., fractures). Thus, we identify individual fractures from clusters of air-dominated voxels by grouping the voxels that have 26-fold connectivity, the most conservative type of connectivity in three dimensions. We then calculate the geometric properties of the resulting fracture networks in both the high-resolution and low-resolution data using the threshold identified with our method, t_G (**Figure** 3). We also test the influence of changing the selected threshold by -100 and +100 gray values on the calculated fracture network characteristics. We perform this test because the range of gray values over which the second derivative of the fit to the PDF is close to zero, indicative of the boundary between solid and air, spans t_G-100 to t_G+100 (**Figure** 3). Thus, any threshold within this range may be appropriate for segmenting the air-dominated and solid-dominated voxels. Note the threshold, t_G, identified for the high-resolution and low-resolution tomogram differ from each other.

We calculate the fracture geometric characteristics that we have used in previous studies to predict the timing of system-size failure, and thus identify potential precursors to failure [e.g., 12, 13]. Moreover, many other fracture mechanics and digital rock physics analyses depend on the accuracy of these measurements. These characteristics include the fracture volume, surface area, major axis length (indicative of fracture length), and minor axis length (indicative of fracture aperture or thickness). We calculate the major and minor axis lengths of the best-fit ellipsoid using the covariance matrix and corresponding eigenvalues of the fracture.

The histograms of the fracture characteristics indicate that the populations of characteristics generally overlap for the networks derived from the tomograms of varying resolutions (**Figure** 4). The few exceptions to this overlap include the volume of larger fractures, and the minor axis length. The low-resolution data appears to host a few larger (more volumetric) fractures than the high-resolution data (**Figure** 4a). The low-resolution data hosts thicker fractures, with larger minor axis lengths, than the high-resolution data (**Figure** 4d). These histograms indicate that varying the threshold from t_G-100 to t_G+100 does not produce systematic changes in the calculated fracture properties.

To more precisely compare the differences between the extracted fracture characteristics, we now examine the differences between the total porosity, and the mean and maximum of the fracture characteristics (**Figure** 5). The low-resolution data produces a system with 1.1-1.4% porosity, whereas the high-resolution data produces a lower range (0.9-1.05%) of porosity (**Figure** 5a). This difference may arise from the hallows of darker gray values that surround the biotite minerals in the low-resolution data (arrows in **Figure** 2) that do not appear in the high-resolution data.

The mean and maximum fracture volume, surface area, and major axis length are higher in the high-resolution data than the low-resolution data. However, the mean minor axis length is larger in the low-resolution data than the high-resolution data. In contrast, the maximum minor axis length is larger in the high-resolution data than the low-resolution data. Therefore, although the overall porosity is higher in the low-resolution data, many of the statistics of the fracture characteristics host larger values for the high-resolution data than the low-resolution data. Thus, the high-resolution data reveals more volumetric and longer fractures with greater surface area than the low-resolution data.

Next, we more precisely quantify the observed differences in the fracture characteristics observed in the data with varying resolutions (**Figure** 6). In particular, we calculate the difference between the porosity, and mean and maximum fracture network characteristics observed in the low- and high-resolution data using the threshold, t_G, identified with our segmentation method. This difference is shown as $(v_L\text{-}v_H)/v_H$, where v_L is the value found in the low-resolution data and v_H is the value found in the high-resolution data. Thus, negative values indicate that $v_L > v_H$.

The porosity and mean minor axis length are the only characteristics for which the values from the low-resolution data are greater than the high-resolution data, $v_L > v_H$ (**Figure** 6). The low-resolution porosity is 29% higher than the high-resolution porosity. The mean fracture properties differ by smaller percentages than the porosity: surface area (27%), major axis length (12%), minor axis length (11%), and volume (8%). The maximum fracture properties tend to differ by larger percentages than the mean properties: surface area (44%), minor axis length (29%), volume (20%), and major axis length (13%). Thus, calculations of the fracture surface area from tomograms are likely to be the most inaccurate of the selected fracture characteristics, rather than the volume or axes lengths.

3.2. How noise influences the characteristics of the extracted fracture network

To further constrain how the calculated fracture characteristics may deviate from the true values in X-ray tomography data, we next produce segmented images with added synthetic noise from the high-resolution data. This noise reflects two types of noise that arises during X-ray acquisition due to X-ray scattering (point-source noise) and limited optical focusing (blurring noise). From these noised images, we then calculate the fracture network characteristics and compare the differences in these values across differing levels of noise. This comparison reveals how each type of noise influences the calculated characteristics, and thus how these calculated characteristics differ from the true values.

We adopt the procedure of 47 to produce the synthetic tomograms. This procedure includes segmenting the original tomogram into fractures and solid, scaling this binary field by the mean gray value of the original tomogram, and then adding noise to the segmented data. After we add noise to the segmented data, we consider these noised-images as synthetic representations of a tomogram with a continuum of gray values that are not yet segmented. Then, to calculate the fracture characteristics of the noised tomograms, we calculate a new global threshold for each of the noised images following our method, described in Section 2.3 (**Figure** 3).

We expect that the influence of noise on the high-resolution data mirrors that of the low-resolution data. Thus, we only test the influence of noise on the high-resolution data. We apply noise to the two-dimensional slices of the tomogram at each z-coordinate (height above the base). So, we first extract two-dimensional, horizontal slices of the segmented high-resolution volume (**Figure** 3). Then we scale this binary field by the mean of the gray values of the original three-dimensional tomogram, following [47]. This scaling increases the similarity between the distribution of gray values of the original image and the noised images [47]. Thus, when the added noise parameter, n, is 0, only two gray values exist in the image (**Figure** 7), with the larger value corresponding to fractures.

3.2.1. Point-source noise

To add point-source noise, we build normal distributions of random numbers with a mean of zero and standard deviations of increasing value with increasing n. We then add these random numbers to the segmented image to simulate the addition of point-source noise to the tomogram. To calculate[JM8] the applied standard deviations of the normal distributions of random noise, we find the standard deviation of the original tomogram, *s*, and then multiply *s* by 0.5 (*n*=1), 1 (*n*=2), 2 (*n*=3), 3 (*n*=4), 4 (*n*=5) and 5 (*n*=6) (**Figure** 7). The parameter *n* is not a value used to calculate the applied standard deviation, but only a method of labelling the synthetic tomograms.

The calculated fracture characteristics are nearly identical in the tomograms with added point-source noise, except when *n*>3 (**Figure** 8). Above this threshold of noise, the fracture network appears to host less volumetric fractures, with lower surface areas, and lower major axis lengths. The added point noise thus acts to dissect the true fractures so that the detected fractures appear smaller.

3.2.2. Blurring noise

Next, we examine differences in the fracture characteristics in tomograms with varying degrees of blurring noise. This type of noise reflects the distortion of the tomogram that could arise from the limited resolution of the optical system. We create these synthetic images by segmenting the original image using our method (**Figure** 3) and then applying a filter with a 2D Gaussian smoothing kernel of increasing standard deviations with increasing *n* (**Figure** 9). We increase the applied standard deviation, *s*, from one to 16 in increments of three such that when *n*=1 then *s*=1, *n*=2 then *s*=4, *n*=3 then *s*=7, *n*=4 then *s*=10, *n*=5 then *s*=13, and *n*=6 then *s*=16.

Increasing the blurring noise produces fracture networks that appear to host less volumetric fractures with lower surface area, shorter major axes and thicker minor axes (**Figure** 10). Blurring thus thickens and shortens the detected fractures.

4. Discussion

In this analysis, we compare differences in the geometric properties of fractures in tomograms at two spatial resolutions and varying degrees of noise. To summarize our analysis and discuss its implications, we now compare the influence of these parameters on the porosity (**Figure** 11). We calculate both the total porosity of the tomogram (three-dimensional porosity), and the porosity of individual horizontal slices along a vertical profile parallel to the longest axis of the cylindrical core sample (two-dimensional porosity). We calculate the two-dimensional porosity in order to quantify how the porosity varies throughout the tomogram, and thus how the observed fracture network varies. Because the three-dimensional porosity of the tomogram provides one specific value representative of the complete system, we may more directly compare the influence of resolution to the influence of noise.

Examining the trends in the three-dimensional porosity indicates that increasing the resolution decreases the porosity, in contrast to expectations (**Figure** 11a). The lower resolution data may produce higher calculated porosity because some voxels were incorrectly labelled as fractures using the segmentation method. Although some misclassification may also exist in the high-resolution data, the low-resolution data appears to suffer from the darker voxels between different minerals to a greater extent than the high-resolution data. For example, the biotite minerals (colored yellow in **Figure** 2) often host a halo of darker voxels. This halo is an artefact of the phase contrast that is not as significant in the high-resolution data. As a result, our segmentation method misclassifies these voxels as fractures, producing the circular structures in the low-resolution segmented data (arrows in **Figure** 2a) that do not occur in the high-resolution segmented data (**Figure** 2g). These artefacts help produce the 0.05% higher range of porosity of the low-resolution data (**Figure** 11a). Analyzing the absorption data, rather than the phase contrast data, may have produced varying results. However, we used the phase contrast data in this analysis because these data were less noisy than the absorption data. Such artefacts may also be removed manually, if the size of the data is sufficiently low. We did not remove them here because such manual removal is not feasible for a typical X-ray synchrotron experiment in which we acquire 50-100 tomograms.[JM9]

Increasing the point-source noise increases the porosity, as expected. This trend is expected because adding point-source noise involves increasing the gray values of the segmented, synthetic tomograms. Because higher values represent fractures in these noised images, increasing the gray values of the solid makes them appear closer to the gray values of the fractures. Thus, in images in which higher gray values represent fractures, noise that increases the gray value will tend to misclassify solid as fractures. Similarly, in images in which lower gray values represent fractures, noise that artificially decreases the calculated gray level may cause voxels to be misclassified as solid. In tomograms, some select a gray scale assignment in which the solids have higher gray levels than air/fluids. Thus, point-source noise that increases the gray value in such tomograms with solids of higher gray levels may tend to lead to the misclassification of fracture-dominated voxels as solid, and thus lower porosities, in contrast to the synthetic tomograms analyzed here.[JM10]

Increasing the blurring noise decreases the porosity in our synthetic tomograms. This trend occurs because the two-dimensional Gaussian blurring noise tends to decrease the gray value (**Figure** 9). Thus, more voxels are misclassified as solid because the solid has a lower range of gray values than the fractures. Similar to the trend with the point-source noise, if the gray scale range is lower for air/fluids than solids, then blurring noise that reduces the gray value will tend to increase the porosity in such tomograms.

The range of tested values of tomogram resolution, added point-source noise, and added blurring noise suggests that the degree of noise may exert a greater influence on the calculated fracture properties than the resolution (**Figure** 11a). However, this conclusion depends on the amount of noise in a given tomogram. If point-source noise produces histograms of gray values similar to the highest values tested here (**Figure** 7), then the calculated porosity may be more than three times higher than the true porosity (**Figure** 11). If blurring noise produces histograms of gray values similar to the highest values tested here (**Figure** 9), then the calculated porosity may be near zero, and thus less than the true value (**Figure** 11).

Examining the trends in the two-dimensional porosity calculated in each horizontal slice indicates that this porosity distribution follows similar trends as the porosity calculated from the three-dimensional tomograms. In both dimensions, increasing point-source noise increases the porosity and increasing blurring noise decreases the porosity.

With the vertical distributions of two-dimensional porosity, we may observe the regions of the tomograms that differ the most in porosity between the low- and high-resolution data. In particular, the volume of the high-resolution tomogram between 1200-1400 voxels above the base (z-coordinate) reaches more than 2% porosity, while the rest of the tomogram appears to host porosity near 1% (**Figure** 11b, c). In contrast, the vertical distribution of porosity observed in the low-resolution tomogram does not host such a spike in porosity from 1200-1400 voxels, but instead ranges from 1-2% porosity across the full height of the tomogram. Note, we report the height throughout both tomograms using the voxel dimension of the high-resolution tomogram. Examination of the two-dimensional slices of the tomograms between 1200-1400 voxels shows that this portion of the tomogram hosts thin fractures that are visible (and thus detected) in the higher-resolution data, but not in the lower-resolution data (**Figures** 2, 3).

This example underscores that the largest fractures that are below the resolution of the tomograms have the most significant impact on the inaccuracy of the calculated properties. Rocks with many small fractures and pores, and only a few fractures with dimensions above the resolution, will produce the most inaccurate fracture network properties. Thus, we may use the distribution of the size (volume or area) of the fractures and pores observed in other datasets, such as Scanning Electron Microscopy images, to constrain the magnitude of the inaccuracy of the calculated fracture characteristics and resulting porosity. If such datasets indicate that the rock hosts a wide range of fracture sizes, with many fractures with dimensions below the spatial resolution of the tomogram, we expect larger differences between the true and calculated porosity and fracture geometric characteristics than if the data set has a narrow distribution of fractures with dimensions above the spatial resolution. Rocks that tend to have a narrower range of pore and fracture sizes with dimensions above the spatial resolution may include higher porosity (25%), well-sorted sandstones, limestones and other rocks composed of cemented grains [e.g., 52, 53, 54, 55]. In contrast, lower porosity rocks, such as granite, may tend to host a wider range of fracture sizes that overlap the spatial resolution, and thus produce calculated fracture properties that are the most inaccurate.[JM11] Consistent with this idea, an analysis of the influence of spatial resolution on the physical properties of porous rocks, including sandstone, limestone and carbonate, found that the spatial resolution has minimal influence on the calculated properties [56]. Similarly, tomograms of two resolutions of Berea sandstone yield different porosities, surface area and tortuosity, but similar permeabilities [57]. Thus, the smallest pores that were only detected in the higher resolution tomogram did not significantly influence the calculated permeability of the system.[JM12]

Our analysis indicates that decreasing the spatial resolution produces the most inaccurate calculations of the surface area, rather than the volume or axes lengths (**Figure** 6, **Figure** 12). Thus, calculations that depend on the fracture surface area, such as those used for estimates of the kinetics of chemical reactions during fluid-rock interactions [58, 59, 60], may have wider error ranges than calculations that depend on the volume, fracture length or aperture, such as the stress intensity factor [e.g., 61]. Thus, calculations that depend on the surface area should be used with greater caution than calculations that depend on the other fracture properties.

Similar to the influence of resolution, the presence of point-source noise has the most significant impact on the calculated fracture volume and surface area (**Figure** 8, **Figure** 12). However, the presence of blurring noise has the most significant impact on the calculated fracture volume, without a strong influence on the surface area (**Figure** 10, **Figure** 12). Thus, when tomograms contain significant amounts of point-source noise and blurring noise that cannot be removed through image pre-processing techniques, the fracture volume and surface area will contain greater error ranges than the minor and major axis lengths.

Due to the significant influence of noise on the properties calculated from tomograms, denoising algorithms are particularly useful to apply before the segmentation of a fracture network. In our analyses, we denoise the volumes using a non-local-means filter [50]. There is a wide variety of other denoising algorithms and software available [62, 63].–[JM13]

5. Conclusions

To quantify how the spatial resolution and noise influence the fracture characteristics calculated from X-ray tomography data, we acquired two overlapping tomograms with spatial resolutions that differ by an order of magnitude during a triaxial compression experiment on granite. We compare the fracture network characteristics calculated from both tomograms of differing spatial resolutions, and from synthetic tomograms with two distinct types of noise. In contrast to expectations, the lower resolution tomogram appears to host higher porosity (1.1-1.4%) than the higher resolution tomogram (0.9-1.05%). The presence of halos of darker voxels surrounding minerals, an artefact of phase contrast, contributes to this unexpected result. However, this analysis reveals that some regions of the tomograms host many thin fractures that are below the resolution of the low-resolution data and above the resolution of the high-resolution data. In these regions, the calculated porosity in the high-resolution data is twice that of the porosity of the low-resolution data, consistent with expectations. Thus, when the fracture network contains many thin fractures, the lower-resolution data may miss more than 50% of the true fracture network. Therefore, the size distribution of the fractures and pores of a rock helps constrain the magnitude of inaccuracy of the porosity and fracture network characteristics calculated from tomography data.

The influence of added noise on the fracture characteristics is stronger than the influence of spatial resolution, using the ranges of spatial resolutions and noise tested here. The addition of point-source noise, which may arise due to X-ray scattering, tends to increase the porosity in our synthetic images in which higher values represent fractures. The point noise tends to dissect the true fractures so that the detected fractures appear smaller, with lower volumes, surface areas, lengths, and apertures than the true fractures. The addition of blurring noise, which may arise due to the limitations of the optics or due to the reconstruction algorithm, tends to decrease the porosity in our images. Blurring tends to thicken and shorten the detected fractures, producing observed fractures that are less volumetric, with lower surface area, shorter major axes, and thicker minor axes than the true fractures. In X-ray tomography data in which lower gray values represent fractures, these trends would be reversed.

The fracture property that differs the most between the fracture networks calculated in the low and high-resolution data is the fracture surface area, rather than the volume, length, or aperture of the fracture. This result suggests employing a larger degree of caution when using equations that depend on the fracture surface area calculated in X-ray tomography data, rather than equations that use the other fracture properties.

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Figure Captions

Figure 1. Fractures extracted from low-resolution (blue) and high-resolution (red) tomograms in a core of Westerly granite deformed within the HADES apparatus on beamline ID19 at the European Synchrotron Radiation Facility. Leftmost 3D synchrotron X-ray microtomography image shows the full core captured in the low-resolution data. Ellipse at the top of the core shows the upper piston of the deformation apparatus. The high-resolution tomogram (0.65 µm/voxel side length) covers a small subvolume of the low-resolution tomogram (6.5 µm/voxel side length).

Figure 2. Example slices of low-resolution (a, c, e) and high-resolution (b, [JM14]d, f) tomograms oriented perpendicular to σ_1, at three example heights (z-coordinate) above the base of the tomogram in a granite sample. The slices are colored by the gray values of the tomogram, which depend on the X-ray energy and material density (i.e., linear attenuation coefficient). Thus, higher values (yellow to light green in the figure) correspond to minerals of varying density (biotite, quartz, K-feldspar, and plagioclase), and lower values correspond to fractures and pores (dark blue). The white arrows in a), c), and e) show the dark rims around biotite grains produced by the phase contrast in the low-resolution dataset. These dark rims may be

misclassified as pore space because they host gray values that overlap the range of the gray values of the pore space.

Figure 3. Method of selecting the appropriate gray level threshold to identify voxels dominated by solid and by air (i.e., fractures and pores) (a) for the low-resolution (b) and high-resolution (c) tomograms, and resulting segmentation of example slices (d-g). In the example segmented slices (d-g), the solid-dominated voxels (with gray values above the threshold) are blue and the air-dominated voxels (with gray values below the threshold) are yellow.

Figure 4. Histograms of geometric characteristics calculated for the high-resolution (solid lines) and low-resolution (dashed lines) fracture networks derived from segmenting the 3D data using a range of thresholds. We calculate the volume (a), surface area (b), major axis length (indicative of fracture length) (c) and minor axis length (indicative of fracture aperture) (d) of all the fractures. The sketches in (c) and (d) show that the major and minor axes lengths (highlighted with blue arrows) are calculated from the best-fit 3D ellipsoid of the fracture derived from the covariance matrix and corresponding eigenvalues. The threshold t_G is the threshold derived using our method, for either the low-resolution or high-resolution data (**Figure** 3). We calculate the fracture characteristics with thresholds from t_G-100 to t_G+100 because the inflection point between the two gaussian distributions of the solid- and air-dominated voxels (where the second derivative is close to zero) includes this range.

Figure 5. Porosity (a) and mean (blue) and maximum (red) fracture characteristics (b-e) calculated from the high-resolution (solid lines with circles) and low-resolution (dashed lines with triangles) data using segmentation thresholds from t-100 to t+100. We calculate the porosity (a) and mean and maximum of the fracture volume (b), surface area (c), major axis length (d) and minor axis length (e) of all the fractures.

Figure 6. Difference in the porosity (black), and mean (blue) and maximum (red) fracture network characteristics observed in the low- and high-resolution data using the threshold, t_G. This difference is shown as $(v_L-v_H)/v_H$, where v_L is the value found in the low-resolution data and v_H is the value found in the high-resolution data. Thus, negative values indicate that $v_L > v_H$. Note, the differences for the maximum values are all negative.

Figure 7. Example slices of tomogram with increasing magnitudes of added point-source noise (a-f) and corresponding histograms (g). The example slice is a horizontal slice (perpendicular to σ_1) at the coordinate z=1253 voxels above the base of the tomogram. When the added noise parameter, n=0, only two values of the gray values exist in the image (g). With increasing

n, the distributions of gray values surrounding these values broaden, producing wider ranges of values that are fractures and wider ranges that are solid material.

Figure 8. Histograms of geometric characteristics calculated for the fracture networks derived from synthetic images with point-source noise. Increasing noise parameter, *n*, indicates increasing point-source noise. We calculate the volume (a), surface area (b), major axis length (indicative of fracture length) (c) and minor axis length (indicative of fracture aperture) (d) of all the fractures.

Figure 9. Example slices of tomogram with increasing magnitudes of added blurring noise (a-f) and corresponding histograms (g). The example slice is a horizontal slice (perpendicular to σ_1) at the coordinate z=1253 voxels above the base of the tomogram. Blurring tends to decrease the range of gray values because the smoothing kernel overlaps increasing amounts of smaller gray values, indicative of solid material, rather than higher gray values, indicative of fractures and pores.

Figure 10. Histograms of geometric characteristics calculated for the fracture networks derived from synthetic images with blurring noise. Increasing noise parameter, *n*, indicates increasing blurring noise. We calculate the volume (a), surface area (b), major axis length (indicative of fracture length) (c) and minor axis length (indicative of fracture aperture) (d) of all the fractures.

Figure 11. Differences in three-dimensional porosity (a), and two-dimensional porosity (b-e) due to differences in resolution (a-c), and differences in noise (a, d-e). The three-dimensional porosity is the total porosity of the tomogram. The two-dimensional porosity profiles (c-e) are calculated from individual horizontal slices at varying heights above the base of the tomogram. We report the height throughout both tomograms using the voxel dimension of the high-resolution tomogram for simplicity.

Figure 12. Influence of each parameter on the calculated fracture properties relative to the values measured without noise in the highest resolution tomogram (a). b) Lowering the resolution influences the surface area the most of the fracture properties, producing the largest normalized magnitude of the difference between the mean value measure in the low-resolution data, v_L, and the high-resolution data, v_H: $|v_L - v_H|/v_H$. c) Point source noise produces the largest differences in the volume and surface area, measured with the normalized difference in the mean value measured in the tomogram without noise, v_0, and at the highest level of tested noise, v_n: $|v_n - v_0|/v_0$. d) Blurring noise produces the largest difference in the volume, as measured with $|v_n - v_0|/v_0$.