Analysis of proppant particles porosity based on microCT image processing

E P Serkova\textsuperscript{1,2}, I V Safonov\textsuperscript{1} and I V Yakimchuk\textsuperscript{1}

\textsuperscript{1}Schlumberger Moscow Research, Pudovkina 13, Moscow, Russia, 119285
\textsuperscript{2}Moscow State University, Leninskie Gory 1, Moscow, Russia, 119991

e-mail: katrin96@inbox.ru

Abstract: The proppant is a granular material with a typical size of 0.2 to 1.2 mm. It is used to prevent the closure of fractures in the reservoir created by hydraulic fracturing procedure, which is actively used in the oil and gas industry. Some types of proppant are manufactured from porous technical ceramics. Presence of internal voids can dramatically decrease the proppant grain mechanical strength and consequently proppant pack conductivity under natural stress. For a detailed study of proppant particles’ internal porosity structure and its relation to the pack’s strength, we applied X-ray microtomography (microCT), which allows to observe this structure non-destructively.

In the work, we presented our approaches for digital analysis of reconstructed 3D microCT images for studying the internal voids and the homogeneity of their distribution inside the proppant. We used an automatic thresholding for primary segmentation of pores and particles. We apply 3D marker-controlled watershed to separate individual proppant particles. We propose features for characterization of radial and layered porosity distribution for each particle and homogeneity evaluation. The correctness of our method was tested on synthetic models. Current results indicate probable dependence of proppant strength properties on its internal porosity, but not on the homogeneity of porosity distribution.

1. Introduction

Nowadays, the technology of hydraulic fracturing of the reservoir is actively used to intensify the oil recovery of the field. This method involves the creation of cracks in rocks by the high-pressure injection of fracking liquid. A granular material (proppant) is pumped into the well together with the liquid wedging the fracture and thereby preventing its closure.

Proppant particles have spherical shapes with a typical size of 0.2 to 1.2 mm. Sand is the cheapest and the most widely used type of proppant. In some cases, the use of proppant with an increased strength of grains relatively to natural sand, or reduced density, seems to be beneficial. Such types of proppant are produced by methods equal to the ones used to create porous technical ceramics from a raw material containing alumina.

In this paper porosity is a dimensionless value from 0 to 1 equal to the fraction of the void space inside proppant particle to particle’s volume. However, the presence of voids within particles decreases their strength characteristics, which can negatively affect the conductivity of the proppant pack in the fracture. For a detailed investigation of the relationship between the internal porous structure of particles and its strength properties, it is necessary to use the methods of introscopy, which make it possible to observe this structure. One of such methods is X-ray microtomography (microCT).
Standard X-ray tomography experiment consists of the following steps. The object under study is illuminated by X-ray beam from various sides with simultaneous registration of resulting 2D shadow projections on the X-ray detector. On the next step, the obtained dataset is processed by reconstruction algorithm(s). In our case the result is the image I (figure 1) with the following characteristics:

3D Image Size: \(~4000 \times 4000 \times 2000\) voxels
Voxel Size: \(1.33 \mu m \times 1.33 \mu m \times 1.33 \mu m\)
Disk Space Size for 2D Slice: 8 MB
Disk Space Size for 3D Image: 15.6 GB

![Figure 1](image1.png)

**Figure 1.** (a) A slice of the reconstructed 3D microCT image and (b) small crop.

Traditionally, the analysis of porosity performed by image processing includes the analysis of total particle porosity, pore size distribution [1] and topology of void space, for example, in the form of pore networks [2]. However, the homogeneity of porosity distribution within an individual particle can also influence the strength properties of the proppant. To test this hypothesis, it is necessary to investigate the voids and the homogeneity of their distribution within the porous ceramic proppant.

2. MicroCT image segmentation

Dense bodies absorb X-ray radiation more strongly than air that is why there is a contrast between ceramic space and voids in microCT image I. The simplest method that gives acceptable results for distinguishing voxels of particles from the background is threshold binarization [3]. After thresholding, we obtain binary image T (figure 2(a)), where voxels of solid are designated by ‘1’ and voxels of voids are designated by ‘0’.

One can see contacting particles in figure 1. Such particles should be digitally separated for analysis of porosity distribution of each particle. The conventional way for the separation of overlapping or contacting convex regions without holes is an application of marker-controlled watershed algorithm [4]. The algorithm is applied to the image with filled internal voids \(I_{B}\). All touching objects are separated, and regions inside particles with filled internal porosity are labeled with unique values (figure 2(b)).

![Figure 2](image2.png)

**Figure 2.** (a) Thresholded image (b) Watershed segmentation result.
3. Porosity characterization

3.1. Description of different porosity values

Proppant particles are porous, and, porosity can be divided into two types: open (or interconnected) and close (or isolated) depending on its connection with the external void space [5]. A pore relates to close porosity when it is not connected with external voids. In its turn, open pores are divide into through and dead-end. Dead-end pore connects only with one of the particle’s surfaces, it is filled with liquid or gas during filtration, but it does not affect the permeability of the porous material. The total porosity includes close and open pores.

Morphological operations are used to obtain images of pores of different types [6]. Each labeled region was converted to binary image \( L \) and processed independently from each other.

An image \( L_{\text{CP}} \) containing only close pores can be obtained from formula (1).

\[
L_{\text{CP}} = L_{3Dh} - L,
\]

where \( L \) is a 3D binary image, that corresponds to a label, \( L_{3Dh} \) is the result of holes filling on 3D image \( L \).

Image \( L_{\text{TP}} \) containing both close and open pores can be obtained from formula (2).

\[
L_{\text{TP}} = L_{2Dh} - L,
\]

where \( L_{2Dh} \) is the result of holes filling of each 2D slice of image \( L \). It is worth to note, for some tasks 2D slice-wise processing of 3D CT images provides reasonable outcomes, for example in [7]. So, we need to remember about 2D operations too, when we process a volumetric image.

Image \( L_{\text{OP}} \) that contains only open pores can be obtained from formula (3).

\[
L_{\text{OP}} = L_{\text{TP}} - L_{\text{CP}}.
\]

The following algorithm should be applied to classify each open pore into a through or dead-end:

1. Let \( L_{\text{OPi}} \) – an image of the i-th connected region on \( L_{\text{OP}} \).
2. Let \( D_{\text{OPi}} \) – the result of dilation of image \( L_{\text{OPi}} \).
3. Find all connected regions on image \( (D_{\text{OPi}} - L_{\text{OPi}}) \) AND (NOT \( L_{2Dh} \)).
4. There will be one connected region in case of the dead-end pore.

The following algorithm for estimating porosity distribution inhomogeneity can be applied to all types of porosity.

To reduce the algorithm running time, the image \( I \) is downsampled by 4 times by the method of three-dimensional averaging. The size of downsampled image \( I_D \) is \( \sim 1000 \times 1000 \times 500 \) voxels.

The following steps preserve the total void space volume when the resolution is reduced:

1. Each voxel on image \( I \) is multiplied by 100 (\( I_{100} \)).
2. Image \( I_{100} \) is downsampled by 4 times by the method of three-dimensional averaging.

The values of voxels of image \( I_D \) belong to the set:

\[
\left\{ \left( \frac{i}{64} \right) \times 100 , \ i \in [0,64] , \ i \ - \ integer \right\}
\]

\( I_D \) is turned into an array of weights according to (2).

\[
W = \frac{100 - I_D}{100}
\]

After this conversion, the voxel on image \( I_D \) with the value ‘0’ (absolutely empty) gets the value ‘1’ in the array of weights; voxel with the value ‘100’ (absolutely not empty) gets the value ‘0’; voxels with values from ‘0’ and ‘100’ gets the value of porosity volume fraction.

In such notation, the porosity of the region \( A \) can be calculated according to formula (6).

\[
\varphi_A = \frac{\sum W}{\frac{V_A}{V_A}}
\]

where \( V_A \) is the volume of region \( A \).

3.2. Radial porosity distribution analysis

The question of the voids distribution within porous objects arises during analysis of various materials. For example, in paper [8], an algorithm for analysis of porosity distribution homogeneity along the
The vertical and horizontal axes of the asphalt sample is proposed. The porosity is calculated in the M cross-sections of the sample, and the indices of the inhomogeneity are calculated according to (7).

$$HI_{Lat,Ver} = \frac{1}{M} \sum_{i=1}^{M} \left| \frac{V_i - V_{Avg}}{V_{Avg}} \right|$$

(4)

The indices of the inhomogeneity reflect the deviation of the void distribution from the mean value. Thus, large values $HI_{Lat,Ver}$ indicate a high level of inhomogeneity, a zero value of the index is possible only in the homogeneous case.

In this paper, we propose a measure that unlike $HI_{Lat,Ver}$ indicates not only the degree of porosity distribution within an object but also the "direction" of porosity imbalance. The whole volume of the particle is divided into two equal parts A and B. These parts correspond to just two shells with equal volumes (figure 3(a)).

![Figure 3. Scheme of dividing the particle on (a) two shells; (b) two hemispheres.](image)

Having divided the volume into two equal parts, we can estimate the balance of porosity between them ($\phi_A$ and $\phi_B$). To make this estimation relative, the following transformations are proposed:

$$\phi_\Sigma = \frac{V_A^{(void)} + V_B^{(void)}}{V_\Sigma} = \frac{V_A^{(void)} + V_B^{(void)}}{V_A + V_B} = \frac{V_A^{(void)}}{2V_A} + \frac{V_B^{(void)}}{2V_B} = \frac{\phi_A + \phi_B}{2},$$

(5)

$$\phi_B(\phi_A) = 2\phi_\Sigma - \phi_A,$$

(6)

where $\phi_\Sigma$ and $V_\Sigma$ are the total porosity and volume of particle, $\phi_{A,B}$ and $V_{A,B}$ are porosity and volume of regions A and B. Introducing normalized porosity $\psi_X = \phi_X / 2\phi_\Sigma$, we derive from (2):

$$\psi_B(\psi_A) = 1 - \psi_A$$

(7)

Measured $\phi_B(\phi_A)$ and $\psi_B(\psi_A)$ for image I are demonstrated on Fig. 4.

![Figure 4. (a) Crossplot of interior and exterior shells porosity for image I; (b) the same after normalization. Green line corresponds to ideally homogeneous distribution of porosity in the particle. One red point corresponds to one proppant particle.](image)
Both representations are meaningful. The distance between the point and the green line stands for the degree of inhomogeneity of the particle on both plots. The further the point from the green line, the higher the inhomogeneity. The “direction” of such porosity imbalance depends on whether the point is below or above the line. The proppant is more porous in the center if the point lies below the line.

Unlike the alternative representation, \( \phi_{\beta}(\phi_A) \) shows not only the degree of inhomogeneity but the variation of particle porosity as well. Indeed, to derive the value of \( \phi_{\beta} \), you need to find the projection of the point onto the green line (coordinates of this projection are equal to the total particle porosity).

The benefit of \( \psi_B(\psi_A) \) approach can be a simplistic quantitative measure of radial porosity distribution inhomogeneity. One can see, that all points on figure 4(b) are lying on a single line. Thus, we can introduce the parameter \( \alpha = 2\psi_A - 1 \), that describes studied inhomogeneity in the range \([-1; 1]\). The value ‘-1’ means the particle contains porosity in the peripheral part; ‘0’ – the homogeneous case; ‘1’ – in the central part.

3.3. Porosity layered distribution analysis

The same math can be applied for layered distribution analysis. The particle is divided into two hemispheres (figure 3(b)). The separation plane ideally should maximize the contrast in porosity values of both hemispheres. Common sense suggests defining the vector from the center of particle mass with filled holes to the center of particle mass without filling the holes. Such vector will be a good approximation of a normal for the desired plane.

For testing purposes we evaluate this parameter for three synthetic spherical 3D models (figure 5):

1) Porosity is distributed uniformly and is equal to 50%.
2) Porosity is distributed radially from 80% to 0%.
3) Porosity is distributed over the particle vertically with the linear change from 0% to 30%.

![Model 1](image1.png) ![Model 2](image2.png) ![Model 3](image3.png)

**Figure 5.** Model particles for testing homogeneity measures.

Results for these models are presented in figure 6. As expected, Model 1 provides zero degree of inhomogeneity in both geometries. Model 2 can be considered as homogeneous via layered-type metric, but radial analysis reveals the porosity distribution peculiarity properly. Finally, Model 3 also demonstrates adequate quantitative values.

4. Numerical experiments

Based on the preceding, we created an algorithm, which divided each particle into two thick shells or hemispheres, calculated the porosity inside each and provided both an estimation of the inhomogeneity and the error of this estimation.
4.1. Experiment 1
Proppant particles on microCT images can have different sizes. Therefore, it is necessary to investigate the behavior of the algorithm when analyzing objects of different sizes. For these purposes, a set of model objects (and corresponding images) is created: spheres with different radii from the set \{10, 20, 45, 60, 85, 100, 120\}, when the typical radius of proppant particle is equal to 100 voxels. Values of porosity are divided into three classes: low 0-5%, medium 5-15%, and high 15-30%. The porosity inside each sphere is set randomly, so that \( \varphi_A \) and \( \varphi_B \) have all possible combinations of low, medium and high porosities (9 combinations for each particle). In case of layered analysis, an additional set of random vectors is generated for each particle, which defines the separation plane between regions A and B.

The inhomogeneity measures \( \alpha_{\text{expected}} \) and \( \alpha_{\text{calculated}} \) are calculated for each particle, where \( \alpha_{\text{expected}} \) is calculated according to given \( \varphi_A \) and \( \varphi_B \), \( \alpha_{\text{calculated}} \) is calculated by the algorithm. Then \( \Delta \alpha = |\alpha_{\text{expected}} - \alpha_{\text{calculated}}| \) is calculated and the dependence of this value from the radius of the model sphere is built. The result is presented in figure 7. As expected, the error of calculating the inhomogeneity measure for sufficiently small volumes is large, but as the radius of the object increases, the error tends to zero.

![Figure 6. Evaluation of non-homogeneity of model particles.](image)

| \( \alpha_{\text{radial}}^1 \) | \( \alpha_{\text{layered}}^1 \) | \( \alpha_{\text{radial}}^2 \) | \( \alpha_{\text{layered}}^2 \) |
|---|---|---|---|
| \( \psi_B \) | \( \psi_A \) |

4.2. Experiment 2
The model object is a particle of a ceramic proppant randomly selected from a microCT image with filled internal pores. The pores inside the particles are distributed homogeneously so that the total porosity of the particle coincides with the preassigned randomly generated porosity from 0% to 30%.

![Figure 7. The error of inhomogeneity measure calculations depending from the radius of the model sphere.](image)
The value of $\alpha_{\text{expected}}$ for such objects is equal to ‘0’. The algorithm calculated the value of $\alpha_{\text{calculated}}$ and $\Delta \alpha$. As expected, the error of inhomogeneity measure calculations $\Delta \alpha$ was close to 0 in all cases.

### 4.3. Experiment 3

Now pores are spherical objects with different sizes that are placed inside the model objects from experiment 2. Pores are placed in a special way to verify the correctness of inhomogeneity “direction” determination. Indeed, for particles, which have more pores in its central part, the value of $\alpha_{\text{radial}}$ was positive, the value of $\alpha_{\text{layered}}$ was equal to ‘0’.

### 5. Results

Thus, the proposed parameter $\alpha$ is a simple quantitative measure of porosity distribution inhomogeneity of corresponding geometry. This parameter was evaluated for eight different microCT images of ceramic proppant. The values of $\alpha_{\text{radial}}$ and $\alpha_{\text{layered}}$ were calculated for each particle on each image. Table 1 summarizes achieved values for all images. It is clearly seen, that all samples tend to be more porous in the central part. The highest effect is observed in image №4, while the most homogeneous images №3 and 7.

| Image № | $\alpha_{\text{radial}}$ | $\alpha_{\text{layered}}$ |
|---------|-----------------|-----------------|
|         | $\mu \pm \sigma$ | $\mu \pm \sigma$ |
| 1       | 0.26 ± 0.15     | 0.09 ± 0.07     |
| 2       | 0.24 ± 0.09     | 0.08 ± 0.07     |
| 3       | 0.15 ± 0.04     | 0.02 ± 0.02     |
| 4       | 0.37 ± 0.10     | 0.09 ± 0.05     |
| 5       | 0.22 ± 0.09     | 0.06 ± 0.03     |
| 6       | 0.29 ± 0.10     | 0.05 ± 0.03     |
| 7       | 0.16 ± 0.18     | 0.09 ± 0.05     |
| 8       | 0.20 ± 0.08     | 0.04 ± 0.03     |

### 6. Conclusions

The demonstrated differences in the properties of internal porosity distribution inhomogeneity of the proppant particles are of interest from a technological point of view. The analysis that was carried out on the available quite small set of images reflects the relationship between the average internal porosity and the laboratory-determined proppant strength characteristic, without revealing a clear dependence with measures of homogeneity. Nevertheless, the proposed inhomogeneity measures are planned to be used in further studies with a larger number of samples.

The layered analysis did not reveal any notable deviations from the homogeneous structure of the proppant internal porosity. At the same time, slice-by-slice analysis shown that the relative error in estimating particle porosity by evaluating its single cross section on a two-dimensional microscopic image can reach dozens of percent (the maximum error in reviewed data was close to 50%).

It should be noticed that the developed tool can be used to analyze the inhomogeneity of the distribution of any dense inclusions within bodies of arbitrary shape as well.

### 7. References

[1] Vogel H J and Roth K 2001 Quantitative morphology and network representation of soil pore structure Adv. Wat. Res. 24(3) 233-242
[2] Dewers T A, Heath J, Ewy R and Duranti L 2012 Three-dimensional pore networks and transport properties of a shale gas formation determined from focused ion beam serial imaging Int. J. Oil Gas Coal T. 5(2-3) 229-248
[3] Otsu N A 1979 Threshold selection method from gray-level histograms IEEE Trans. Syst. Man Cybern. 9(1) 62-66
[4] Safonov I V, Mavrin G N and Kryzhanovsky K A 2006 Segmentation of convex cells with partially undefined boundaries Pattern Recogn. Im. Analysis 16(1) 46-49
[5] Dullien F A L 2012 Porous media: fluid transport and pore structure (Academic Press)
[6] Soille P 2013 Morphological image analysis: principles and applications (SSBM)
[7] Smelkina N A, Kolsanov A V, Chaplygin S S, Zelter P M, Khramov A G 2017 Pulmonary emphysema recognition by CT scan Computer Optics 41(5) 726-731 DOI: 10.18287/2412-6179-2017-41-5-726-731
[8] Senthilmurugan Thyagarajan L T 2010 The heterogeneity and mechanical response of hot mix asphalt laboratory specimens Int. J. Pavement Eng. 107-121