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# Characterization of Porosity Properties of Carbonate Rocks through a Fast Image Processing Approach

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**Abstract.** The characterization of porous media represents a critical issue for recovering oil and gas from reservoir rocks. Analyses of digital images generated by X-ray micro-computed tomography ($\mu$CT) help build detailed models of rocks and extract petrophysical parameters. For this purpose, we have developed an efficient 2D microtomographic image processing method for the extraction of samples' porous system properties. The proposed method utilizes a histogram-based analysis to perform the segmentation of the images. Our approach allows the automatic computation of the total porosity, pore size distribution, and general pore orientation data of seven limestone plugs from the Eocene Tambaba Formation by the usage of image processing techniques. The porosity values extracted by the new segmentation technique were compared against porosity values obtained through porosimetry (helium) essays. The average error between experimental values (obtained by porosimetry) and the porosity values obtained through the proposed segmentation process is 3,42%. A comparison of pore orientation distribution provided automatically by the proposed technique and the orientation obtained through classical methods showed excellent correlation. Computation time spent for the automatic calculation of pore system properties was approximately 9 minutes per sample (performed in an Intel Core i7 CPU with 8GB of RAM PC). Further experiments of calculations with smaller quantities of slices provided similar petrophysical properties, with a reduction of 95.7% on the processing time. The accomplished results showed the new automatic segmentation technique's great potential for the extraction of porous system properties of calcareous rocks with accuracy and efficiency in computational time.

**Keywords:** Image segmentation, Pore area distribution, Pore size distribution.

## 1 Introduction

The dependence on the use of oil and its derivatives is significant in several economic areas of modern society. Since this is a limited and non-renewable resource, it is extremely important to find ways to maximize the recovery of these materials. Preliminary studies of reservoirs provide information that helps to assess the feasibility of prospecting and strategic planning for the exploration of these natural resources. In addition to the geological composition of the region, it is essential to evaluate some properties of the porous network contained in the rock formation, since the most important aspect that governs the physical behavior of a rock sample is mainly related to its microstructure (Al-Marzouqi [1]). The analysis of petrophysical properties provides data capable of quantifying the storage capacity, distribution and the way in which fluids will flow in the extraction process of these materials (Thomas [2]).

The X-ray microcomputed tomography ($\mu$CT) is a non-destructive technique to obtain petrophysical properties and has great importance as a way to characterize rocks/soils. With technological advances in this field, this technique has become quite relevant due to its ability to accurately represent the internal structure of rocks through virtual models (digital rocks) (Guntoro et al. [3]), offering a deeper understanding of the relationship between pore geometry and the physical properties of rocks.

Part of the success attributed to the $\mu$CT analysis is associated with the advancement of processing algorithms aimed at this type of application (Schluter et al. [4]).From classical segmentation methods (Deng et al. [5]) to modern machine learning algorithms based on neural networks (Yun et al. [6]) have proved to be good computing tools.

As the physical properties are usually obtained from processing the microstructures represented by the 3D reconstruction of the scanned samples (Saxena and Mavko [7]), this makes the analysis of digital rocks demand a lot of computational resources and high processing time (Wu et al. [8]; Saad et al. [9]). On the other hand, approaches based on 2D image processing provide a faster and more efficient alternative for estimating these properties (Saxena et al. [10]).

In addition, due to the specificities of each lithology, it is common that some of the workflow steps require user intervention to determine or verify adjustment parameters. In some cases, as in the analysis of carbonate rocks, the nature of the porous arrangement adds even more complexity to this process. Given that this type of rock stands out for presenting vast spatial heterogeneity of its pores (Smodej et al. [11]). This set of factors makes the process of extracting properties slow, and it can take hours to complete the volume processing (Chauhan et al. [12]).

These factors encourage the research into reservoir characterization techniques, carried out through $\mu$CT, using approaches that provide accurate results, with low processing time. These requirements are a priority due to the fact that the information provided is useful for decision making that directly impact the reduction of losses related to prospecting and the maximization of the extraction capacity in oil and gas reservoirs.

## 2 Related Works

Many efforts have been dedicated to the study of microtomographic image processing for the extraction of physical properties from rocks. Al-Marzouqi [1] surveyed the main characteristics of the approaches used to study digital rocks. The author highlights the conventional work cycle used for the processing of $\mu$CT images, being mainly composed by the steps of acquisition of 3D images, removal of artifacts, image segmentation and calculation of petrophysical properties. This details of operations may vary in its implementation depending on the quality of the images generated and the type of rock evaluated, and may add more complexity to the analysis with the introduction of more filtering and post-processing steps throughout the work cycle (Berg et al. [13]).

Digital rock image segmentation techniques are in constant development. In general, global thresholding techniques showed good results when applied to images free of artifacts and with a high value in the signal-to-noise ratio (Berg et al. [13]). Iassonov et al. [14] presented a comparative study of 14 techniques used to calculate the porosity of samples with different composition. In this study, the Otsu's method was one of the global thresholding techniques that showed satisfactory accuracy for the calculation of porosity.

Some works focused on presenting approaches to improve the characterization of limestone rocks. In order to provide a method to locate and quantify sub-resolution porosity, that is, pores with sizes smaller than the measurement resolution, in carbonate rocks, Smal et al. [15] used an image segmentation technique based on local thresholding for perform this task.

Few works in the literature show information of the processing time demanded by the method applied to digital rocks characterization. Nova et al. [16] showed that the implementation of the approach used, through the execution of the PVE algorithm (Elliot and Heck [17]), took about 2 hours to extract the porosity value for a set of sandstone and limestone plugs. The results presented in the work by Chauhan et al. [12] showed that the duration of the analysis varied between 15 minutes, for the fastest technique (k-means) and 63 hours, using the support vector machine (SVM) algorithm. Although the authors did not carry out a detailed analysis of the times presented in the work, it is known that processing 3D volumes from computed tomography scans may require a large processing time (Ju et al. [18]) due to the amount of data processed and the complexity of the operations executed.

Direct comparison of the processing time between these works cannot always be performed due to the differences between the investigated properties, the available computational resources, the size and complexity of the processed data. As most of the computed properties are based on the 3D microstructures of the scanned samples, processing the 2D slices appears as a way to reduce the computational cost of the analysis. As presented by Saxena et al. [19], Saxena and Mavko [7], it is possible to obtain precise physical properties of rocks, from the analysis of 2D images, quickly and efficiently. The use of this concept can be explored in analogous scenarios as a way to speed up the process of characterization of petrophysical properties.

## 3 Methodology

In this work, seven cores of carbonate rocks were used as object of study for extraction of petrophysical properties by processing the images generated by the scanning process of an X-ray $\mu$CT. Details about the rock samples' origin and the scanning process were described in the works Cardoso et al. [20] and Cardoso [21]. The slices obtained by the volume reconstruction step feed the workflow designed to compute the desired information about the porous structure of the samples.The sequence of operations present in the image processing is shown in Figure 1.

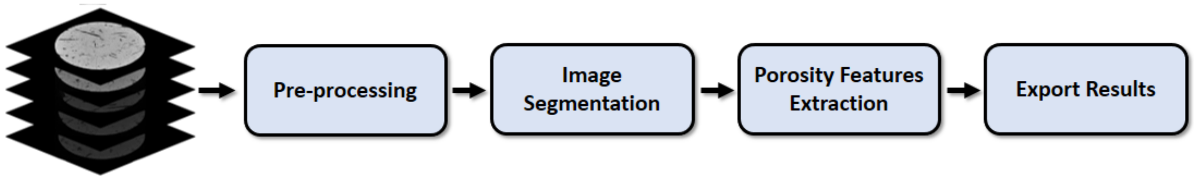



Figure 1. Workflow of the proposed method.

All procedures were implemented in order to provide an autonomous execution of the developed routine. Therefore, the first task solved by the algorithm is to define a region of interest autonomously from the analysis of the position of the projection of the rock on the slice. After that, each slice is imported individually and are carried out through the same set of procedures of filtering, segmentation and porosity features extraction. During the filtering step, a Gaussian filter was applied to reduce noise on images.

A global threshold segmentation algorithm was designed to classify pixels in image according to their intensity. The threshold value used to determine the limit between classes was calculated for each slice, based on the histogram behavior. The next processing module is charged of computing morphological information of the pores detected on each image. The properties gathered cumulatively by the proposed method are the absolute porosity, pore size distribution and pore orientation distribution.

In order to validate the output data, some strategies were adopted according to each feature. The porosity values computed were compared with the values obtained through experiments carried out in the laboratory with a helium gas porosimeter. As a matter of comparison of the calculated pore orientation distribution, the processing of the same set of samples was carried out in parallel using the ImageJ software, applying the Otsu thresholding method as segmentation technique. Pore size distributions were not assessed using numerical indicators.

The workflow was applied to all the slices obtained by the volume reconstruction process. Additionally, it was also applied to a smaller number of slices per sample. At this time, a set of evenly spaced slices were processed as a representation of the volume. This approach is represented in Figure 2. Only 5% of slices were used at this experiment. It was motivated as an hypothesis that it would be possible to reduce the processing time and preserve the accuracy of the analysis. The processing time and porosity results were recorded for all of the experiments.

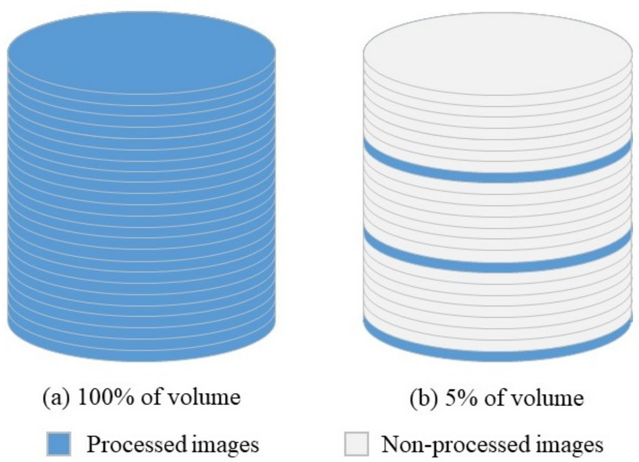



Figure 2. Sampling slices strategy.

# 4 Results and Discussion

This section presents the main results obtained from the application after processing the images through the proposed method, taking 100% and 5% of the $\mu$CT slices of each studied rock sample.

## 4.1 Porosity

The values calculated for the average porosity of the samples are shown in Table 1. The table presents the porosity values obtained computed by the method, using the whole and a fraction number of slices, and the reference values collected from the experiments with the helium porosimeter. It is possible to notice that the segmentation technique implemented for the calculation of porosity resulted in a suitable accuracy for most samples, generating mean errors of 3,42% and 3,41%, when considering 100% and 5% of the slices respectively. The reduced number of processed slices by sample did not affect negatively the porosity computation, when compared with the result obtained by using the whole available data.

Table 1. Porosity results.

| **Sample** | **Porosity (%)** | | |
|---|---|---|---|
| | Method (100%) | Method (5%) | Porosimeter |
| Sample 1 | 13.62 | 13.65 | 16.17 |
| Sample 2 | 15.30 | 15.21 | 24.38 |
| Sample 3 | 21.35 | 21.25 | 27.29 |
| Sample 4 | 17.64 | 17.56 | 21.05 |
| Sample 5 | 23.36 | 23.20 | 22.71 |
| Sample 6 | 24.91 | 24.76 | 24.39 |
| Sample 7 | 27.00 | 27.02 | 25.21 |

## 4.2 Pores size distribution

According to the pores sizes analysis, each pore detected in the segmented image is counted as an instance and its area is recorded individually. Figure 3 shows the comparison of the porosity, regarding the area of the pores, among the samples, by the method that considers only 5% of the images. Given the shown results, we notice how the porous heterogeneity is present on this lithology. It is relatively easy to see that porosity of samples 1, 2 and 4 are mostly composed by pores with small areas. Otherwise, the other samples seem to have a porous network containing a significant number of notorious pores inside their volume.

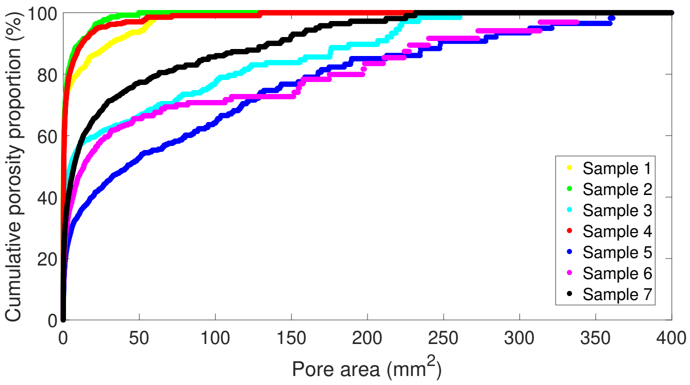


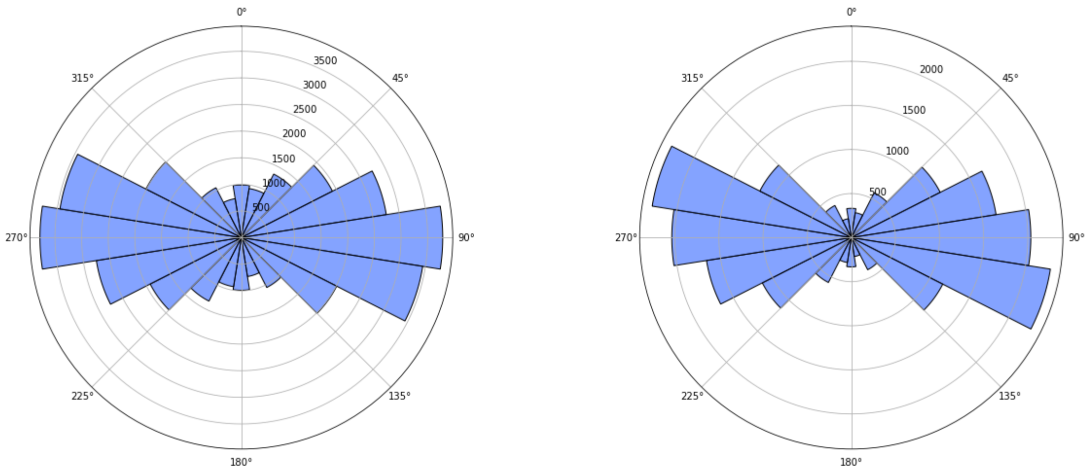

Figure 3. Comparison of the porosity distribution according pores area, considering only 5% of the slices on the analysis.

### 4.3 Pores orientation distribution

In addition to the characterization carried out according to the area, a quantification of the dominant orientation of the found pores was computed. These results are essential to better understand the cases of anisotropy and properly assess conditions related to fluid flow dynamics on the reservoir rock sample. The rose diagrams were used as graphic objects to represent the pore orientation distribution obtained by the proposed technique.

Figure 4 contains the rose diagrams obtained by the proposed method (taking 100% of images) and the validation method. In Figure 4a, it is possible to notice the result of the analysis on the orientation of the pores through the proposed approach. The image on the right, Figure 4, contains the representation obtained using the resources of ImageJ.

Figure 4. Comparison of Sample 7 Large Pore Orientation Diagram.




(a) Proposed method.

(b) ImageJ.

The generated diagrams showed a high degree of similarity between the models obtained and the reference data for most samples. The correlation between the results, expressed by the coefficient of determination (R2), shows that the models found for 5 samples had values above 77%. The good performance of this analysis can be attributed to the similar behavior between the segmentation techniques used generate the diagrams.

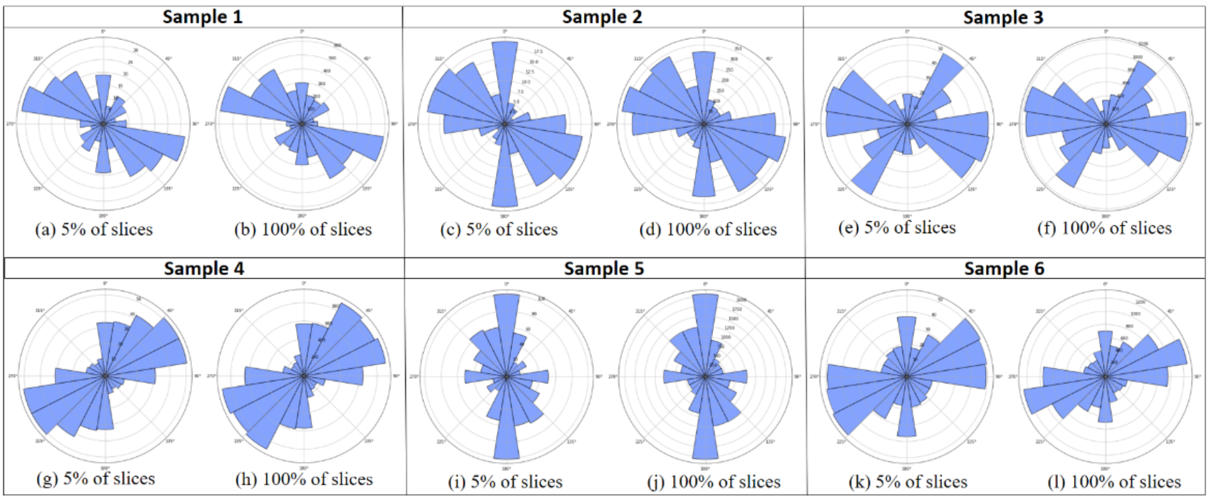



Figure 5. Comparison of orientation distribution of large pores after processing 5% and 100% of images.

To compare the results of the diagrams obtained considering only 5% of the images, their diagrams were compared with the results of the proposed method when considers 100% of the images for the analysis. Only the diagrams with the representation of the large pores were used for their relevance in their physical meaning. It was observed that the directions with greater dominance were preserved in all samples display. Basically, there was only one change of scale in the axes amplitudes, due to the reduction in the amount of pores detected.

### 4.4 Processing time

The processing time of the implementation of the proposed techniques were recorded. The times can be seen in Table 2. The proposed technique took an average time of 8:56s to analyze the data from a sample, using all of the slices. When considered only 5% of the input data, the average time dropped to 23s, which is a tremendous gain of time, with no major damages on the system accuracy. These values were obtained by running on a computer with the following configurations: Intel i7-4500 processor (1.8GHz - 2.4GHz), 8GB RAM memory and Nvidia Geforce 840M GPU. Although present on the computer, GPU processing was not found during the analysis.

Table 2. Time consumed for processing data with the respective method (min:sec).

| | Sample 1 | Sample 2 | Sample 3 | Sample 4 | Sample 5 | Sample 6 | Sample 7 |
|---|---|---|---|---|---|---|---|
| **Prop. Method (100%)** | 11:06 | 6:56 | 9:16 | 13:23 | 5:31 | 3:41 | 12:41 |
| **Prop. Method (5%)** | 0:30 | 0:20 | 0:23 | 0:36 | 0:16 | 0:10 | 0:24 |

## 5 Conclusions

This work presents an approach for extracting petrophysical properties from porous media in 2D microtomographic images of carbonate rocks. The proposed method includes an image-based technique, based on histogram analysis, to calculate porosity values, area and pore orientation. The proposed method was also able to quantify the pores according to their area and express this information graphically, providing additional information about the porosity composition of the rock. In addition to the pore areas, they were also extracted as information on pore orientation.

The results obtained for the analyzed porous network properties had a fair degree of similarity with the presented validation strategies. In addition, the choice of reducing the amount of images analyzed by volume shown to be an likely alternative to increase the efficiency of the system in obtaining these porosity properties. The implementation of fast characterization algorithms plays an important role in the oil industry as it allows the processing of large numbers efficiently.

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**Authorship statement.** The authors hereby confirm that they are the sole liable persons responsible for the authorship of this work, and that all material that has been herein included as part of the present paper is either the property (and authorship) of the authors, or has the permission of the owners to be included here.

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