IMAGE ANALYSIS OF RESERVOIRS ROCK - RESULTS OF SEGMENTATION USING STATISTICAL METHODS

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Abstract. *Determination of physical properties of reservoir rocks is a very important problem for reservoir engineering. These properties can be determined through microscopic image analysis using porous means image processing techniques, implying in reduced costs and greater speeds. In this article we present some statistical segmentation methods applied to a oil reservoir rock image set clustered into geological groups. We also present some fundamental geological concepts for the correct image segmentation. The results present include the binarized images, geological classification and its characterization, that is, the porosity values, autocorrelation and pore distribution curves for different types of samples.*

Keywords*: reservoir rocks, image binarization, image characterization, statistical methods.*

1. INTRODUCTION

The oil exploration and drilling industry needs to determine the physical properties of reservoir rocks. Usually, this properties are determined using lab experiments which take considerable time and usually cost a lot of money. Core in a gas porosimeter is an example of a lab experiment which measures porosity and permeability of the sample. This experiment has a high cost and is destructive, that is, damages the sample.

As technology advances, we can perform computational analysis on drill cutting samples or core (intact or damaged) using a myriad of thin microscopic plates image analysis techniques, which allow us, for instance, to estimate porosity and permeability of reservoir rocks (Bueno, 2001) and (Bueno *et al*., 2002).

There are many advantages of using image analysis techniques on reservoir rocks, among which are the low computational lab assembly cost, the usage of either drill cutting samples or damages core, which are cheap to obtain, and the possibility of reprocessing images already acquired (Fernandes *et al*., 2002).

Binarization is a step in the image processing system that separates the object of interest from the background and its result is the conversion of a gray scale image into a binary one (Gonzalez and Woods, 2008). It differs from simple border detection because it goes beyond detecting frontiers and also differentiates between objects and background, eliminating image artifacts that are conveniently classified into one of the two possible categories.

Image segmentation of non trivial images is one of the most difficult steps in image processing and its accuracy determines whether the computation process will success or fail (Russ, 2002). Therefore, special care must be taken in this step so that good results are achieved.

The most used methods are the statistical ones that rely on grey level histograms for binarization and that can be either manual or automatic. Statistical histogram-based methods found in the bibliography are not universal, that is, they do not achieve good results for all types of images. This is specially important in the case of digital images of reservoir rocks, which have specific characteristics and properties that must be analyzed.

The main problems found in the binarization of images of reservoir rocks using statistical gray level histogram-based methods are the following:

- Different shade for every mineral in the rock. For instance, opaque minerals that do not allow light to pass through, darkening the image may be mistaken for oil spots and vice-versa, which may account for different values of porosity and permeability;
- Converting an image from colors to grey scale may change important information for image interpretation. For instance, calcareous rock images have grains in dark shades that can be mistaken for the resin that fills the pores because the different shades of gray thus obtained are very similar;
- In an image there are very light and very dark grains, which implies in the non existence of a cut value in the histogram that can separate grains from pores.

Therefore, this work intends to binarize images from reservoir rock samples from different geological classifications and characterize those images, determining porosity and permeability values, besides autocorrelation and pore distribution curves.

In order to validate the porosity values, the ones obtained will be compared with those obtained with a gas porosimeter. In this article, two different samples will be evaluated: one from a sandstone (sample P148_K2) and another from a carbonate (sample P262_K441) and the results obtained will be studied. These samples were chosen based on the fact that their geological classification is different and the binarization process achieves very different results between both samples.

This article is organized as follows. In section 2, we present a brief bibliographic review on the areas mentioned in this work. This is followed by a description on the methodology used in this work. In section 4 we compare the binarization results for all methods, as well as the results obtained in the image characterization process. We also include some relevant remarks on both issues and we finish up with section 5, where several conclusions are presented, as well as a comparative analysis between the results previously described and the laboratory (empirical) results.

2. BIBLIOGRAPHY REVIEW

2.1. Reservoir Rocks

Reservoir rocks are the ones whose porosity and permeability allow for oil accumulation. Most known oil reserves are found in sandstones and carbonate rocks, even though oil reserves can also be found in shales, conglomerates and even igneous and metamorphic rocks (PGT, 2007).

Porosity is the relation between the empty space volume and the total volume of a rock (Rosa *et al*, 2006), which, in most reservoirs, goes from 10% to 20%, and absolute porosity corresponds to the total volume of interconnected pores. Porosity can be measured directly in core samples or indirectly, through electric profiles, and can be classified in the following categories:

- insignificant (0-5%);
- poor (5-10%);
- average (10-15%);
- good (15-20%);
- very Good (>20%).

Permeability of a porous environment, usually represented by the letter *k*, is a measure of its ability to let fluids through (Rosa *et al.*, 2006) and is expressed in *Darcys [D]* or *miliDarcys [mD]*. It is defined mainly by amount, geometry and connectivity degree of the pores and can be classified in the following categories:

- low (<1md);
- average (1-10md);
- good (10-100md);
- very good (100-1000md)
- excellent (>1000md).

Most known reservoirs show permeability in the range of 5 to 500md.

Porosity and permeability are directly proportional to the degree of selection and grain size and inversely proportional to its sphericity. Besides, lateral and vertical variations in permeability and porosity are strongly defined by the characteristics of the depositional environment (Suguio, 2003).

Optical porosity is obtained by microscopic images by dividing the image a matrix of pixels and calculating the amount of pores in the total size of the image. The optical porosity varies directly on the used resolution, increasing as the resolution increases.

Experiments in gas porosimeter tend to generate higher values of porosity. This is mainly due to the fact that the gas density is lower than the one of the resin used for impregnation of the sample, and thus gas is able to invade smaller pores, not accessible to resin.

When using image analysis to determine porosity, a satisfactory value for porosity will be one between the gas and optical ones.

2.2. Image Processing System

Global study methods using images usually involves all steps in Fig 1 and these step have a specific and detailed format according to the goal of the undergoing study (Bueno, 2006). In Fig 2 we show the basic steps in digital image processing adapted to the study of porous materials plates. In brief, those steps are the following[1]:

- *Sample obtainment and preparation*: a sample of the material is acquired and transformed into a thin and polished plate with the pores filled with a specific type of resin;
- *Image acquisition*: the image to be studied is acquired using an instrument such as the optical or electronic microscope;
- *Pre-processing:* optional step whose goal is to improve image quality, for a specific goal;

[1] The interested reader can find more details about those steps in (Bueno, 2006).

- *Segmentation*: identify and separate the image objects;
- *Characterization*: extract interesting information, describing object characteristics and classify them and also obtainment of quantitative information for reservoir rocks image analysis, which may include the determination of porosity and the pore size distribution;
- *Recognition and Interpretation*: Patten recognition and object interpretation. In reservoir rocks image analysis processes, assigning meaning to objects may include 3D reconstruction steps and process simulation.

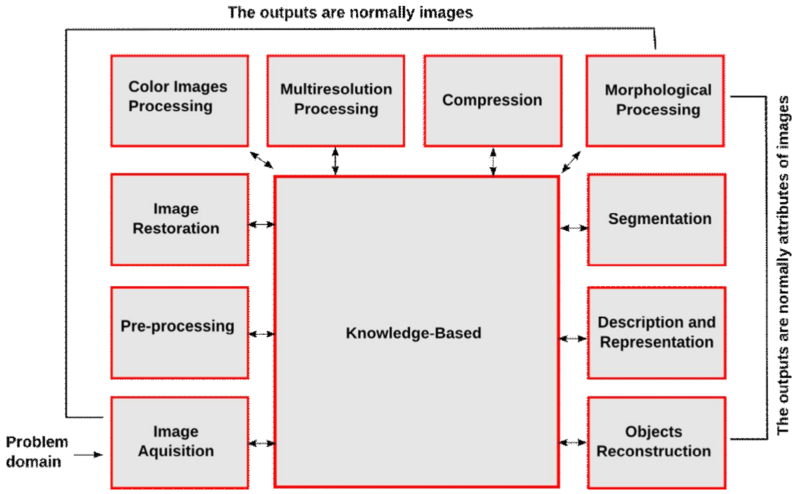


Figure 1. Steps in the global digital image processing method (Gonzalez and Woods, 2008)

Among the many advantages of using images to determine physical properties of rocks, we can highlight the possibility of analyzing a great amount of samples at low cost and the usage of drilling cuts or damaged core samples.

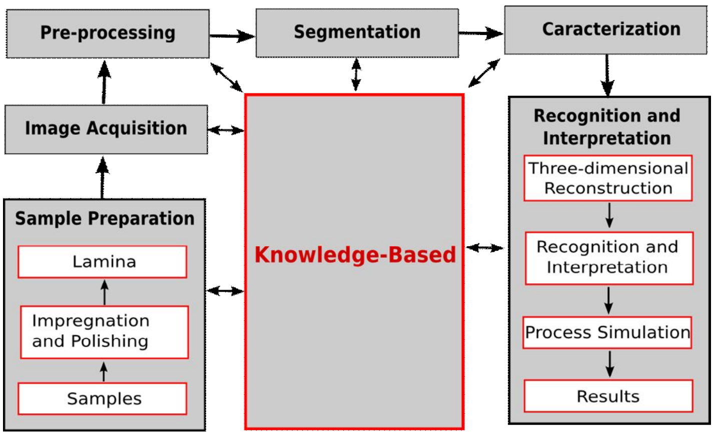


Figure 2. Basic steps in the digital image process adapted to the study of porous materials.

2.3. Statistical Segmentation Methods

In this section we describe briefly the statistical segmentation methods used in this paper. The interested reader can find a more complete description in Rego and Bueno (2008) and the computational algorithms in Parker (1997).

The methods used are the following:

- *Gray level Histograms Method*: the manual method based on grey level histograms in the simplest form of image binarization and is performed by choosing a threshold grey level *Th* as cut point in the histogram as the best separation of the regions under analysis;
- *Mean Value:* Sum all grey level values for each point *(i,j)* in the image *Im(i,j)* and determine the average grey level value (Parker, 1997), which is used as a threshold for region separation;
- *Two Peaks Method:* iterate through the histogram and determine the first peak (grey level with the highest occurrence level). After that, the second peak is determined by multiplying occurrence levels by the square of the distance to the first peak. This method is recommended when the histogram shows two well defined and separated peaks;
- *Johannsen Entropy Method:* this automatic method is based on entropy, that is, the division of grey levels in two parts in order to minimize their interdependence;

- *Thrussel Iterative Method:* an initial threshold value is refined through consecutive iterations over the image, using the calculated average level in each class to improve the threshold level determination (Thrussel, 1979 apud Parker, 1997).
- *Otsu Variance Method*: it is based on the selection of the smaller point between two histogram peaks using the concept that object pixels and background pixels have different average levels and are random number obtained from two different normal distributions, with different standard deviations and variances (Otsu, 1979 apud Parker, 1997).

3. METHODOLOGY

The statistical methods analysis presented in this paper is the first step of a masters dissertation in oil engineering whose goal is to develop a specific binarization method for the study of reservoir rocks. This step intends to binarize a set of microscopic images in order to evaluate each method's efficiency for each of the available geological group of reservoir rocks images.

The results achieved for each different method can be of very low quality for certain types of reservoir rocks because these rocks show very different characteristics for each geological classification. For instance, one method can achieve good results for sandstones and low quality ones for a carbonate. Besides, in many samples there are oil spots which make it more difficult to differentiate between pore and grains.

As discussed in the previous section, the statistical methods tested in this work are: binary, mean value, two peaks, Thrussel Iterative, Johannsen's Entropy and Otsu variance. All these methods share the main characteristics of relying on grey levels histogram. They are described in details in (Parker, 1997) and implemented in C++ programming language in the LIB_LDSC library.

3.1. Samples

The images used in this work are reservoir rock sample images supplied by CENPES/Petrobras.

Reservoir rock classification, either as sandstones or carbonates, is made through a careful evaluation performed by the operator through the microscope. Usually, this operator is a geologist or someone knowledgeable in this field of study. It is very difficult to describe an image without access to its petrographic plate. The many minerals with different colors, textures, cleavages, the varied behavior of light incidence and oil (hydrocarbons) remains can be very confusing even for an experienced professional.

Therefore, given the fact that we do not have the mineral description and pore count performed when the image was acquired, we decided for describing the images just in the porous and granular phases. There are 22 samples that we clustered according to their geological similarity in 7 groups, in a total of 290 images.

In this article, the binarization results will be shown for two different samples: one sandstone (sample P148_K2) and one carbonate (sample P262_K441). These samples were chosen because they have dissimilar behavior after conversion for gray levels. The P148_K2 sample, after its conversion, shows a lighter granular phase while the P262_K441 shows a lighter porous phase. This means that after binarization with statistical methods, at least one of them will show an inverted result.

3.1.1. P148_K2 Sample

Sandstone with structure in light tones, few oil spotted grains and oil filled pores and blue resin filling the porous space (Fig 3). It can be seen that the image is bluish, which is caused by the type of light used in the microscope when the image was acquired.

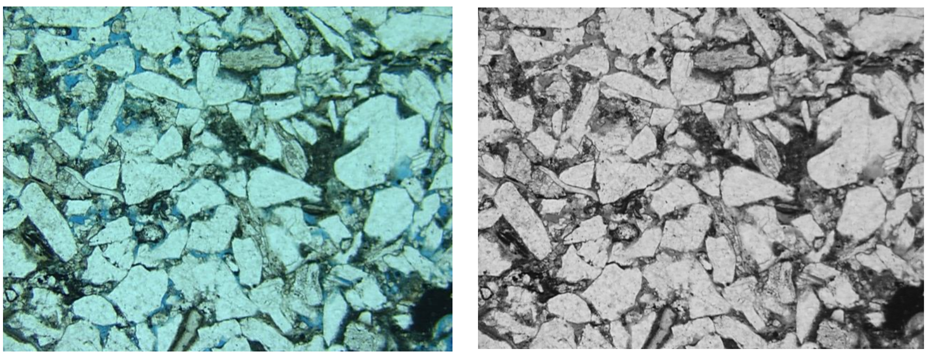


Figure 3. Color and grey level images for the P148_K2 sample

3.1.2. P262_K441 Sample

Carbonate with ooliths in dark tones, a few grains with lighter tones involved by the ealochemical in dark shades and pores filled with blue resin (Fig. 4).

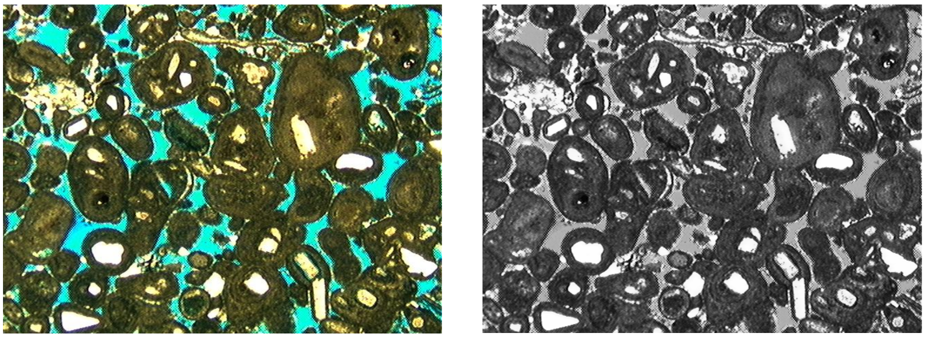


Figure 4. Color and gray level images for the P262_K441 sample

All experimental physical properties obtained for these samples are presented in Table 1 and were give by CENPES/Petrobras together with the images.

Table 1. Experimental physical properties for the samples.

Samples	*Image resolution* *($\alpha[\mu m]$)*	*Gas porosity* *($\phi_g[m^3m^3]$)*	*Optical porosity* *($\phi_o[m^3m^3]$)*	Number of images
P148_K2	4.545	14.8	3.37	6
P262_K441	6.0	26.2	15.6	10

3.2. Software and Hardware

This section describes the hardware and software used in this work. The programming language used was C++ compiled by g++ in the *Fedora 9* operational system. The machine used was a *Sun Ultra 40*, with 4 *Dual-Core AMD Opteron* processors, 12*Gb RAM* memory and 215*Gb* hard disk.

The image repository was saved in a data server accessed through SVN which was available to our research group in geoinformatics at LDSC lab. This server has 4Gb RAM memory and 2 *AMD Opteron 850* processors.

The softwares used were the following:

- *LIB_LDSC:* Class library development in the C++ programming language by the Porous Means and Termophysicial Materials Properties Lab (LMPT) at the Mechanical Engineering Department at UFSC. LIB_LDSC has a large number of classes for the development of software's in image processing, which includes from basic image classes to advanced pre-processing, segmentation, labeling, reconstruction and graphical filters. For our work, we used the basic image classes and image binarization filters.
- *IMAGO:* Image analysis technology specialized in engineering problems, mainly in the micro structural characterization and physical property determination through simulations areas. It was developed by the ESSS group (*Engineering Simulation and Scientific Software*) in partnership with the LMPT lab and CENPES/Petrobras. Imago was widely tested in the determination of petrophysical properties from petrographic images (Gaspari, 2003) e (Philippi *et al.*, 2000).

In this work IMAGO will be used to characterize binarized images, determining porosity, autocorrelation and pore distribution curves so that comparison and validation of binarization methods can be performed.

3.3. Implementation Details

In this section we describe this work's implementation details.

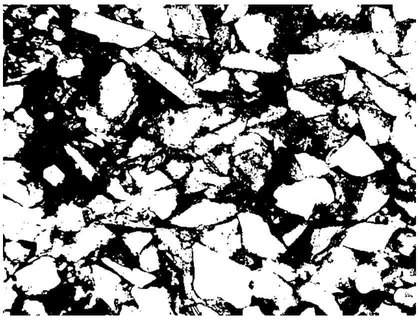
- *Clustering the images into groups:* the images were classified as sandstones or carbonates, given their similarity based on tone, granulometry, grain disposition, opaque or oil-spotted grains and the presence of oil in the porous space;
- *Creation of the images repository:* a separate repository was created for each type of sample (for instance, P148_K2, P262_K441) in order to store all the results of the image processing steps. The directory structure was created to store images and data for all the steps of the image processing systems, from the original image to its reconstruction, including simulations, data sheets, graphics and reports;

- *Image pre-processing:* the first step of pre-processing was converting the images from the TIF format to the PGM one, with 256 gray levels, with the *convert* command in a shell script that received all image names from the terminal and used no compression in order to cause no information loss. The second step was image edition to remove black borders that were not part of the samples but yet a characterization step artifact. This step was not subject to automation due to the fact that borders were different in size and lateral presence (sometimes they were in a single side, sometimes in both).
- *Images binarization:* a C++ method was developed for binarization using LIB_LDSC classes. This method received as input a file with the images names and binarized them according to the selected method, saving the resulting images in the PBM format. In reservoir rocks binarized images granular phase was represented by the white color and the porous phase, by the black color.
- *Images characterization:* The IMAGO software was used on the binarized images to determine porosity, autocorrelation and pore distribution curves according to the following steps:
  - Conversion of PBM images into the TIF format (IMAGO reads only the latter and the binarization process results in the former format)
  - Definition of image resolution
  - Porosity calculation, with the result saved in a text file;
  - Autocorrelation calculation with the graphic generation and resulting data exported to a text file;
  - Pore distribution calculation with the graphic generation and resulting data exported to a text file.

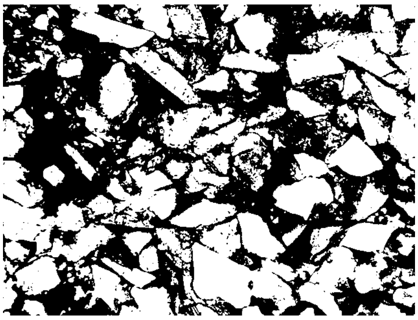
4. Results

In this section we present the results of the digital image binarization process for both samples (P148_K2 and P262_K441) using all six methods described in section 2.3. After the binarization, all images were characterized in order to determine their porosity values, autocorrelation and pore distribution curves, as described in details in the previous section.

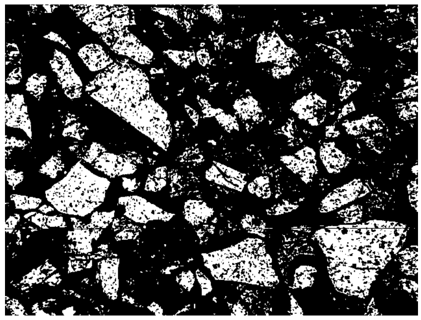
4.1. P148_K2 Sample



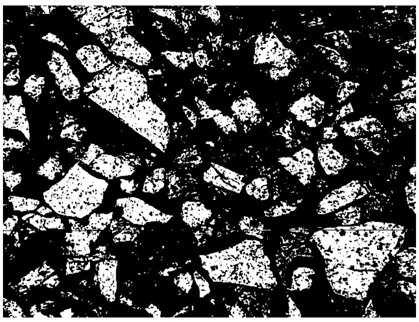
(a) Binary (image 3271i13)



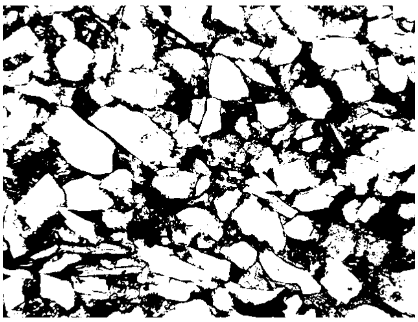
(b) Mean Value (image 3271i13)



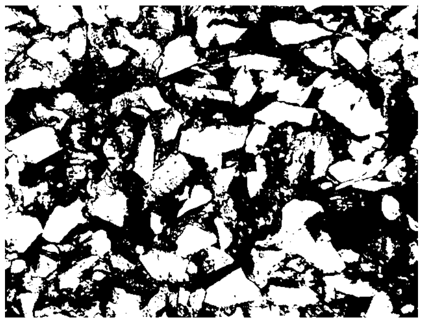
(c) Two Peaks (image 3271i09)



(d) Johannsen's Entropy (image 3271i09)



(e) Thrussel Iterative (image 3271i07)



(f) Otsu Variance (image 3271i14)

Figure 5. Binarization results for the P148_K2 sample[2].

[2] Figures were chosen due to their result being similar to the average of the samples.

Table 2. Average porosity for the P148_K2 sample

Number of Images	Binary	Mean Value	Two Peaks	Thrussel Iterative	Johannsen's Entropy	Otsu Variance
18	44.49	47.03	74.69	38.29	73.84	45.21

Table 3. Porosity for the P148_K2 sample

Images	Binary	Mean Value	Two Peaks	Thrussel Iterative	Johannsen's Entropy	Otsu Variance
3271i01	33.968	41.536	63.909	22.974	63.909	36.554
3271i02	41.184	44.323	71.877	30.836	71.877	41.184
3271i04	43.531	46.224	76.196	37.326	76.196	44.119
3271i05	47.464	48.026	-	-	-	46.886
3271i06	48.241	48.241	87.574	41.583	86.619	47.320
3271i07	44.079	46.477	76.555	38.382	76.555	44.338
3271i08	43.807	46.558	76.322	37.784	76.322	44.349
3271i09	39.584	45.336	74.762	34.544	74.462	42.279
3271i10	42.250	44.604	71.495	33.063	71.495	41.259
3271i12	42.407	46.422	76.376	37.600	76.376	44.180
3271i13	44.826	47.503	78.125	40.501	78.125	46.167
3271i14	45.315	47.603	80.807	40.231	80.807	45.887
3271i15	46.394	48.836	96.416	43.398	86.775	47.990
3271i16	47.290	48.816	90.617	44.036	90.617	48.211
3271i17	48.358	48.981	-	-	-	48.031
3271i18	51.924	51.367	8.239	51.924	7.277	52.204
3271i19	49.347	49.661	88.534	43.419	86.499	49.661
3271i20	40.702	46.007	77.558	35.100	77.558	43.171
Standard Deviation	4.08	2.21	18.88	6.30	18.40	3.54

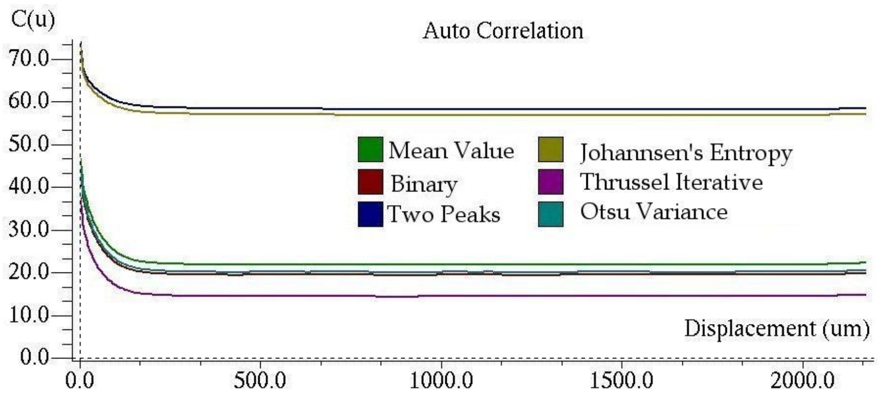


Figure 6. Autocorrelation Curve for the P148_K2 sample

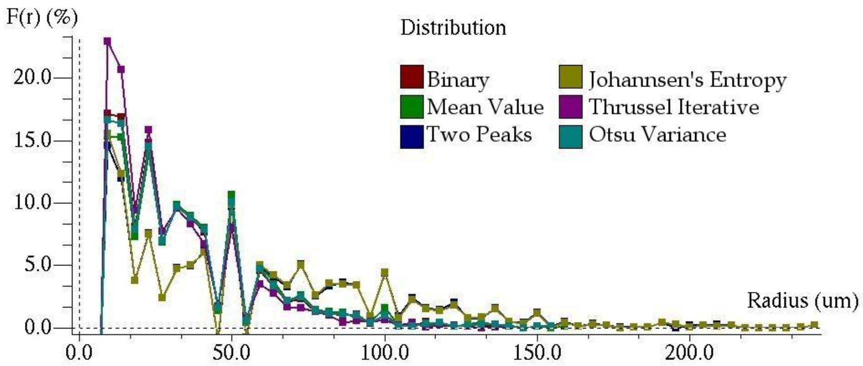
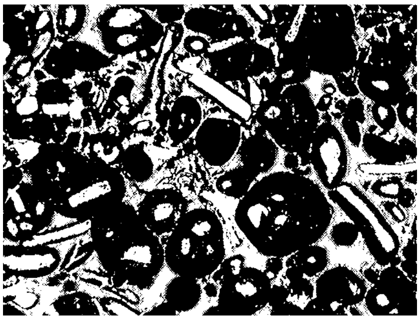


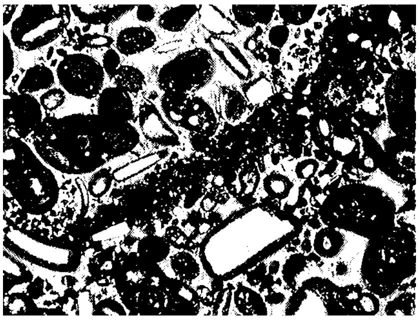
Figure 7. Pore Distribution Curve for the P148_K2 sample

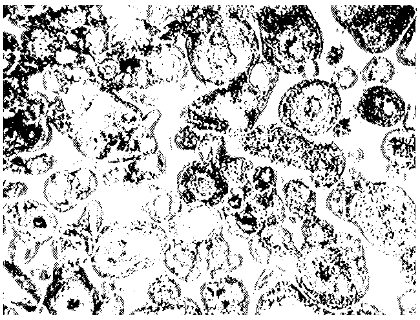
4.1.1. Results evaluation

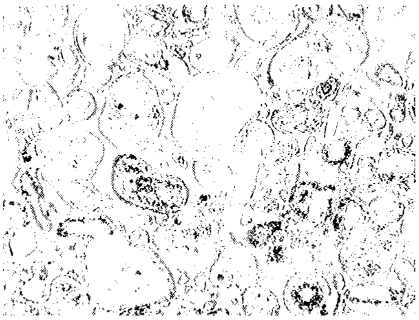
- Digital images in this sample do not show great complexity, given the facts that the porous and granular phases are very different, there are not many oil spotted or dark grains which could render the binarization more difficult;
- For images 3271i05 and 3271i17 the methods Two Peaks, Thrussel Iterative and Johannsen's Entropy produced results in which the value of the porosity was 100%, representing an error in the binarization. Thus these results were not used to represent the average porosity;
- All porosity results were similar, with the exception of the Two Peaks and Johannsen’s Entropy methods;
- The best results were obtained with the Binary and Mean Value methods;
- The experimental results obtained for this sample were 14.8 for gas porosity and 3.37 for optical porosity. The best result was achieved by the Binary method (44.49) had an error close to 200,6%. Therefore, it is safe to say that no method found a value close to the experimentally determined values;
- The autocorrelation curve (Fig 6) shows that all results are similar, with the exception of Two Peaks and Johannsen’s Entropy’s curves, which stay below the other curves and must be discarded;
- The pore distribution curve shows that approximately 15% of the pores have a diameter between 10 and 15μm.

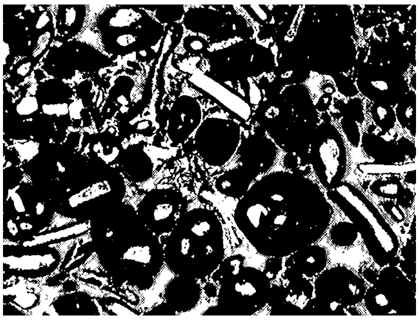
4.2. P262_K441 Sample


(a) Binary (L67409i3)


(b) Mean Value (L67409i8)


(c) Two Peaks (L67409i6)


(d) Johannsen’s Entropy (L67409i2)


(e) Thrussel Iterative (L67409i5)

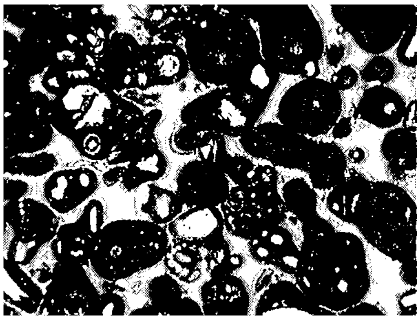

(f) Otsu Variance (L67409i6)

Figure 6. Binarization results for the P262_K441 sample

Table 4. Average porosity for the P262_K441 sample

Number of Images	Binary	Mean Value	Two Peaks	Thrussel Iterative	Johannsen's Entropy	Otsu Variance
10	69.51	65.95	24.48	76.83	7.92	73.63

Table 5. Porosity for the P262_K441 sample

Images	Binary	Mean Value	Two Peaks	Thrussel Iterative	Johannsen's Entropy	Otsu Variance
L67409i1	75.971	68.095	28.546	80.297	8.269	77.146
L67409i2	73.657	67.094	9.243	77.791	7.720	74.882
L67409i3	69.434	64.785	39.668	74.387	5.950	71.098
L67409i4	76.415	69.243	18.546	81.361	7.520	78.748
L67409i5	67.297	64.771	38.802	76.091	13.020	71.523
L67409i6	65.525	65.030	24.606	-	8.264	73.327
L67409i7	66.386	66.677	17.716	78.216	7.001	75.871
L67409i8	68.045	65.565	27.960	75.814	6.061	73.270
L67409i9	67.347	64.829	20.682	74.674	8.762	71.450
L67409i10	65.037	63.403	19.071	72.829	6.640	68.965
Standard Deviation	4.05	1.7	9.06	2.8	1.92	2.88

4.2.1. Results evaluation

- Digital images in this sample are very complex for the binarization process, given the fact that granular phase has light and dark grains and porous phase has an intermediate tone. When the gray scale conversion was performed, the resin that fills the pores takes a lighter shade than the darker grains, a fact that automatic methods cannot detect. As a result, we have an image where darker grains are considered as pores and lighter grains and porous phase are considered grains.
- For image L67409i6 the method Thrussel Iterative produced results in which the value of the porosity was 0.27%, representing an error in the binarization. Thus these result were not used to represent the average porosity;
- No method achieve a reasonable visual result.
- In spite of the fact that Two Peaks method's results are very similar to the gas porosity, the interpretation of what is a pore and what is a grain is erroneous and therefore no method obtained a result that can be considered as really similar to experimental porosity;
- For these samples, no autocorrelation and pore distribution graphics were not evaluated, since binarization did not result in a satisfactory interpretation of porous and granular phase. These results show that statistical automatic methods cannot be used in the binarization of reservoir rock images with different shades of granular phase without the assistance of an experienced operator.

5. CONCLUSION

After binarizing and characterizing the samples previously described in this article, in order to analyze the different binarization methods previously described and we came to the following conclusions:

- For images whose porous and granular phases are distinct and where the porous phase is darker that the granular phase, the statistical methods that show the best results are the binary and mean value methods;
- Two peaks and Johannsen's Entropy methods showed the worst results for all samples, in the Two Peaks case this method is recommended when the image has background and object well defined and a bimodal histogram with two separated peaks.
- For complex images whose granular phase has both lighter and darker shades, none of the evaluated methods returned a satisfactory result. In this case, an experienced user could either work with conjugated separation of

the objects of interested using different binarized images or work with local methods, but, local methods are slower, consume more memory and require training for the operator. The human eye is more prone to errors and in may sometimes bias negatively the operator judgment and the automatic methods try to eliminate these human errors.

Given all those facts, we can arrive at conclusion that there is no automatic method that shows good results for all kind of samples, given that they could not find the correct patterns in those images.

Another important aspect is that the methods that working with gray levels images will always produce worse results than working with color images because color images have more information about this image (Fig 3 and Fig 4). A color image is represented by 24 bits or 16777216 colors while a gray image is represented by 8 bits, only 256 shades.

Therefore, future work in this problem includes the development of a binarization method for colored images using neural networks that can solve all the problems that are specific of reservoir rocks. The idea is to develop a method that can understand not only the complexity of the problem, but also specific image characteristics so that it can be applied to all different types of reservoir rocks. Such development is under way and has yet to show final results for publication, but has already returned some promising preliminary results that indicate the probable correction of this idea.

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7. RESPONSIBILITY NOTICE

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