

Automatic analysis of tomographic 3D picture of cores from well drilling

As part of Projects of Signal and Image Processing

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1. ABSTRACT

In the petrology context, this project aims at presenting, comparing and implementing on Matlab different tomographic 3D image processing methods in order to extract usable oil volume information inside the rock. Those information are obtained by analysing vacuole and fault network of the image. Those methods are mathematical morphology, variational method and local anisotropy method. A pre-processing phase is needed before each process. According to the results, variational method is more performed for fault extraction and mathematical morphology method for vacuole extraction. Functions are implemented on a Matlab graphical interface.

2. INDEX TERMS

Anisotropic filter, Laplacian filter, Wavelet transform, Curvelet transform, structure tensor, erosion, dilatation.

3. INTRODUCTION

Tomography is an imaging technique allowing object internal structure visualization without any superposition of under and over lying structure that deteriorates the conventional image projection. This has found a widespread application in many scientific fields including medicine, chemistry, astronomy and petrology. Our study is focused on petrology application, based on 3D drilling forage core images. 3D image is a block of 192 2D binary images of a slide which size is 450×312 pixels.

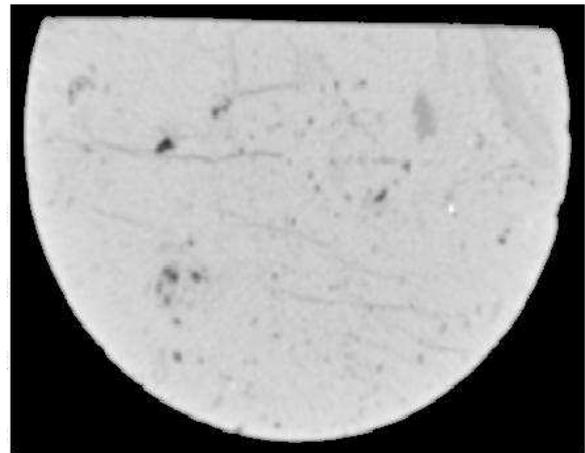


Figure 1: Tomographic image of cylindrical core

The purpose of this study is to determine the ground degree of workability in oil extraction. Several methods to extract vacuole and fault network information are implemented. Algorithms are synthesised on Matlab.

4. RAISING AND IMPROVING PICTURE

Segmentation, analysis's optimisation and reliability are achieved by an image's pre-processing. Original images are noised and low contrasted, those require a pre-processing.

4.1. Noise treatment

Noise processing is the first pre-processing step. It is performed to avoid a noise misinterpretation as a fault or a vacuole. The noise has to be identified in order to achieve an efficient process. To do so, multiple filter types can be used as mean, Gaussian or median filters. By testing main filter types on images, the best one is selected. The Gaussian filter is the most efficient one.

After the filter selection, the most effective parameter configuration has to be found. It is a critical step because if the filter parameters are not precise enough noise elements and fault could be merged. Then some faults can be filtered or some noise elements are not removed, consequently the detection process is detracted.

The faults have a directional structure whereas the noise elements haven't. That introduces an isotropy idea. The use of a directional insensitive filter is needed to solve that problem. The Gaussian filter is not. That is why the "Pérona & Malik" filter is selected. It is the first and most used anisotropic filter. It filters elements which gradient is less than a pre-defined threshold. This threshold is completed by a constant integration which sets filtered intensity. In this way, noise could be removed and faults could be conserved in the same time.

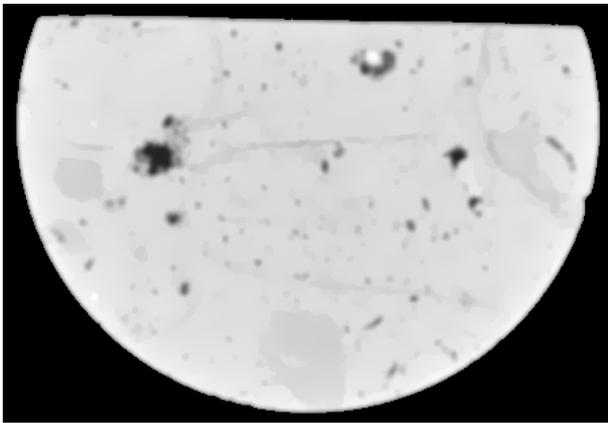


Figure 2: Noiseless image

4.2. Contrast raising

After noise filtering, image's contrast needs to be raised. This step must be performed only on a noiseless image, otherwise noise would be raised.

Contrast raising is performed by using Laplacian filter. It consists in adding the high-filtered picture to the original picture. Therefore, image outlines are raised. This filter is set by a single parameter which increases (or decreases) the ratio between the high-filtered image and the original one. That means that the most important is the k constant, the most raised are the image outlines.

Image's contrast raising is illustrated on the next figure.

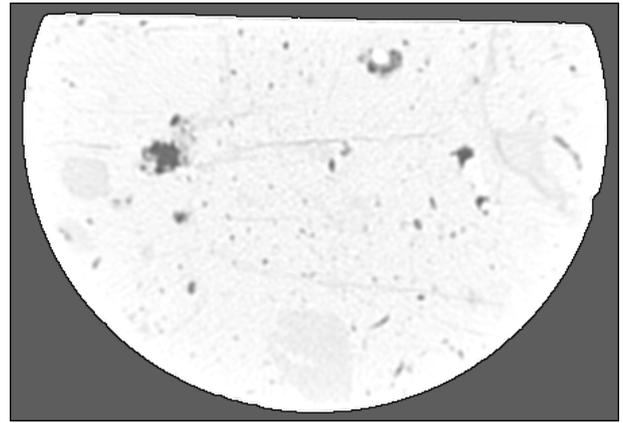


Figure 3: Image with raised contrast

Filtered and raised picture is ready to be worked by others modules like segmentation or analyse.

5. MATHEMATICAL MORPHOLOGY METHOD FOR DETECTION

Vacuoles and faults have opposite structure. Mathematical Morphology (MM) can be defined such as a theory for analysis of the spatial structures and also as a powerful technique for the image analysis.

The goal of this method is to provide a quantitative description of geometrical structures such as their boundaries, their skeletons and their convex hulls. The Mathematical Morphology is considered as a non-linear approach in digital image processing that has made excellent results in the feature detection of interest in digital images.

The Mathematical Morphology has two basic operators, erosion and dilatation, from which all others morphological operations are derived. Here are presented the definitions of those two operators.

5.1. Binary Erosion

Erosion of a binary image f by structuring element b is defined as:

$$\varepsilon_b(f) = f \ominus b = \bigcup_{x \in I^2} \{b_x \subseteq f\} \quad (1)$$

This definition indicates that the structuring element b slides in the image and compares the surrounding area of each pixel in the vicinity of the central point (which in most cases corresponds to the physical center of structuring element) and preserves the pixel neighborhood where it matches.

5.2. Binary Dilatation

The expansion of a binary image in a serie f by structuring element b is:

$$\delta_b(f) = f \oplus b = \bigcup_{x \in I^2} \{\bar{b}_x \cap f \neq \emptyset\} \quad (2)$$

This definition indicates that when the structuring element is examining the image, the vicinity of the central point should be a possible intersection with the relevant points of the image, making it so that more pixels are captured.

The tomographic images used were in tone of gray which is quite different. However the theoretical principle applied to binary images remain the same for the images in tone of gray.

5.3. Erosion in Tone of Gray

$$\varepsilon_b(f)[x, y] = f \ominus b = \min_{(\tau, v) \in B} \{f(x + \tau, y + v) - b(\tau, v) : (x + \tau, y + v) \in f\} \quad (3)$$

This erosion aims at verifying that the structuring element is centered at x below the function f, since it is not defined at a point where the structuring element is above the signal f.

The effects of erosion in gray levels are:

- ✓ darken the image;
- ✓ expand and widen the valleys;
- ✓ connect nearby valleys;
- ✓ reduce and sometimes eliminate peaks;
- ✓ separate nearby peaks ;

The visual result of the eroding image in gray levels presents itself with a reduction of the peaks and extends the dark regions as illustrated in Figure 4.

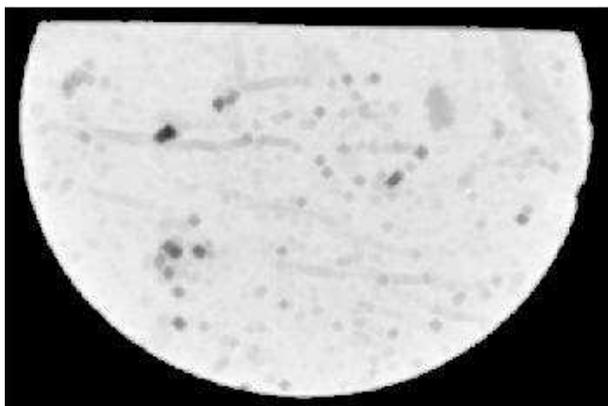


Figure 4: Eroded image

5.4. Dilatation in Tone of Gray

$$\delta_b(f)[x, y] = f \oplus b = \max_{(\tau, v) \in B} \{f(x + \tau, y + v) + \bar{b}(\tau, v) : (x + \tau, y + v) \in f\} \quad (4)$$

The effects of expansion in gray level are:

- ✓ lighten the image;
- ✓ extend the peaks (light standards);
- ✓ connect nearby peaks;
- ✓ reduce and sometimes eliminate valleys (dark standards);
- ✓ separate nearby valleys.

The visual result of the dilated image in levels of gray presents itself with decreases in valleys and expanding in light regions.

5.5. Vacuole detection

Vacuoles and faults, due to their specific totally different form, are easily separable by a simple combination of those two operators.

Erosion with a circle would destroy the linear forms (faults) and a dilatation with the same dynamic rebuilds the non linear form with a quite similar shape. This is the easiest technique to obtain vacuoles. However, the main problem of this technique is that some faults are larger than the small vacuoles. To suppress them, these small vacuoles have to be removed.

This dilemma is illustrated in the following figures.



Figure 5: Figure Erosion and dilatation with an important structural element: we obtained most of the vacuoles

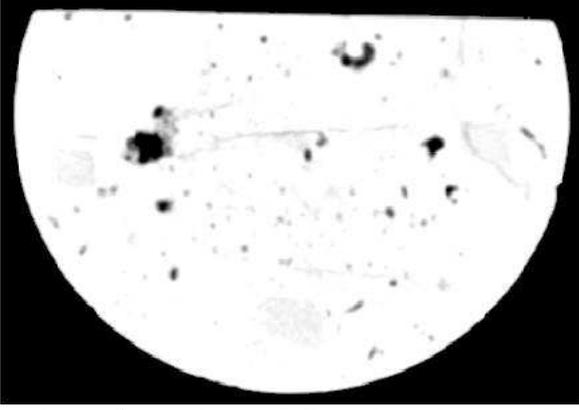


Figure 6: Erosion and dilatation with a small structural element: some faults remain

A second option is to use the reconstruct function with Matlab. This function erodes with a mask, and by comparing the result with the original one, this reconstructs the undestroyed elements. The main effect is that the dynamic between the vacuoles and the faults is more important than with the previous method. Also vacuoles are identical to their initial form. It remains though we still have the conflict between the large faults and the small vacuoles.

The increased dynamic is revealed by the picture histograms.

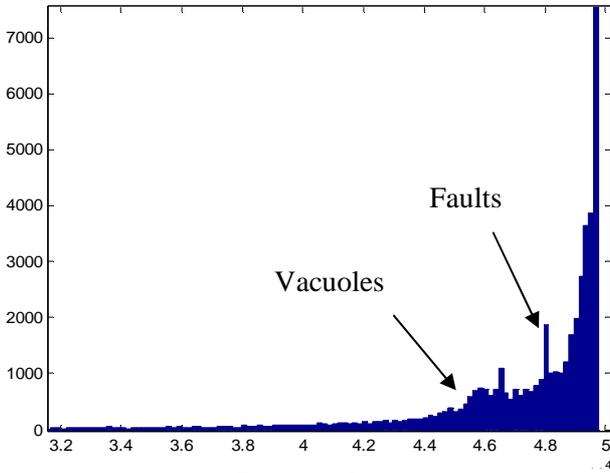


Figure 7: Image histogram

We can now set a threshold to obtain the entire vacuoles without any fault.



Figure 8: After thresholding, there are only vacuoles

The same method using a line as a structural element with the proper orientation is not so efficient to extract the faults, it is due to important gray elements not identified as vacuoles.

6. LOCAL ANISOTROPY METHOD FOR DETECTION

The second method that is applied to extract information from images is the structure tensor method. It is based on the local orientation of each element from the picture.

6.1. Principle

In mathematics, the structure tensor, also referred as the second-moment matrix, is a matrix derived from the gradient of a function. It summarizes the predominant directions of the gradient in a specified neighborhood of a point, and the degree to which those directions are coherent. That's why this approach could be interesting in order to detect faults.

A discrete array of samples $I[p]$ is considered to represent a bi-dimensional image, where p is a couple of coordinates. The 2D structure tensor is given as follows:

$$Sw[p] = \sum w[r] S_0[p-r] \quad (5)$$

S_0 is a matrix such that

$$S_0[p] = \begin{bmatrix} (I_x[p])^2 & I_x[p]I_y[p] \\ I_x[p]I_y[p] & (I_y[p])^2 \end{bmatrix} \quad (6)$$

I_x represents the x-axis gradient, I_y the y-axis gradient, and $w[r]$ is a fixed "window weight" that depends on r , such that the sum of all weights is 1.

6.2. Interpretation

The fundamental interest of the structure tensor S_w comes from its eigenvalues λ_1, λ_2 (which can be ordered so that $\lambda_1 \geq \lambda_2 \geq 0$) and the corresponding eigenvectors e_1, e_2 . Indeed, they summarize the distribution of the gradient of the corresponding pixel p .

Indeed, assuming that $\lambda_1 \geq \lambda_2 \geq 0$, two cases appear :

- If $\lambda_1 > \lambda_2$, then e_1 is the direction maximally aligned with the gradient.
- If $\lambda_1 = \lambda_2$ the gradient in the window has no predominant direction, for example when there is a circular form within that window.

The attribute which is associated to the eigenvalues can be quantified by the **coherence**, defined as :

$$c_w = \left(\frac{\lambda_1 - \lambda_2}{\lambda_1 + \lambda_2} \right)^2 \quad (7)$$

This quantity is 1 when the gradient is totally aligned and 0 when it has no preferred direction. That is why the structure tensor method seems to be appropriate to our problem because coherence equal to 1 is expected for a fault structure.

6.3. Results

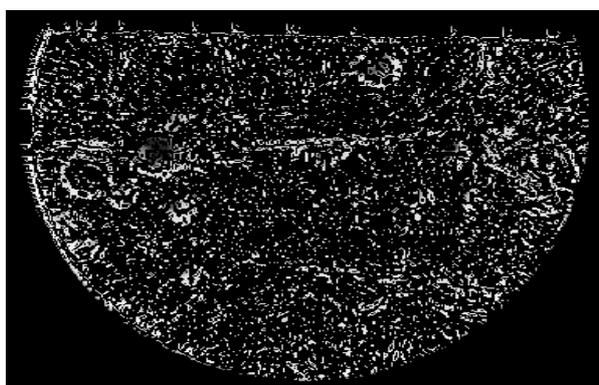


Figure 9: Structure tensor process

In this resulting picture, too many noise elements are detected. So to conclude, this method is not efficient enough to process the fault and vacuole extraction because a noise element could be extracted instead of an interesting structure.

6.4. A variant from the structure tensor method

Another variant from the structure tensor method is developed to extract particular structures in the image. It consists in creating an accumulation image with the gradient direction straight line.

Indeed, for each pixel, the director angle is known because, thanks to the structure tensor, the gradient predominant direction is known. So, for each pixel, the straight line associated to the gradient direction is known and the pixels belonging to this straight line are activated. By showing the accumulation picture of all the straight lines, we can identify and extract some particular structures.

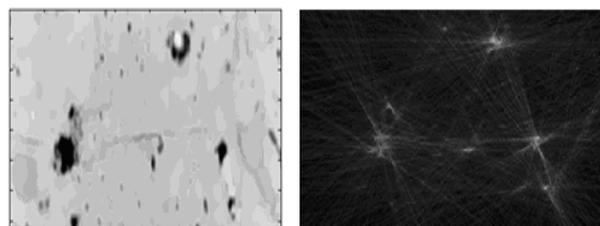


Figure 10: Variant from the structure tensor process

The straight lines cross on several point of the image. It means that on these points, elliptic or circular structures are detected. In other terms, the vacuoles are detected.

This variant cannot detect the fault structures and doesn't give exact information about the area of the vacuoles. But this method is still interesting because the detection of the vacuole locations in the pictures is made quickly.

7. MATLAB LIBRARY MCALAB FOR DETECTION

Morphological Component Analysis (MCA) of images is currently used in image processing. MCA is a method which separates features contained in an image when these features present different morphological aspects. This method can be very useful for decomposing images into texture and piecewise smooth parts or painting applications.

In order to demonstrate MCA key concepts, the MCALab library has been developed. MCALab is a library of Matlab routines that implements MCA methods.

Here, the MCALab library is used for visualizing independently vacuoles and faults of the rock in the picture.

7.1. Morphological component

A given n-sample image x is a sum of K images $(x_k)_{k=1,\dots,K}$, $x = \sum_{k=1}^K x_k$, having different morphologies. Each x_k is called a morphological component.

Assume that the image x is the linear superposition of K morphological components. The MCA framework aims at recovering the components $(x_k)_{k=1,\dots,K}$ from their observed linear mixture. For each K , the representation α_k of x_k in the transformation (dictionary) Φ_k is the result of the discrimination between content types, preferring the component x_k over the other parts.

Indeed, it consists in choosing an appropriate dictionary in order to have a good decomposition.

7.2. The wavelet transform

The wavelet transform is adapted to represent efficiently isotropic structures. Therefore, it can be used for visualizing vacuoles. Here the symmetrical mother wavelet (symlet) is used to realize the Discret Wavelet Transform on the original picture. It is characterized by one parameter which specifies the number of vanishing moments.

In this study, the reference image section of cores is the following one:

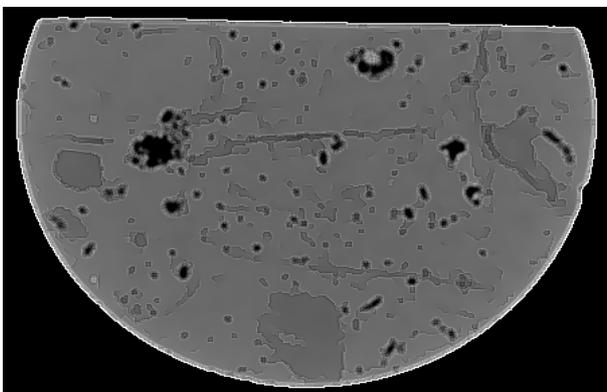


Figure 11 : Image of a section of core

It is important to note that this picture is pre-processed. Now, it is possible to apply the

MCALab decomposition, using the wavelet transform on this image:

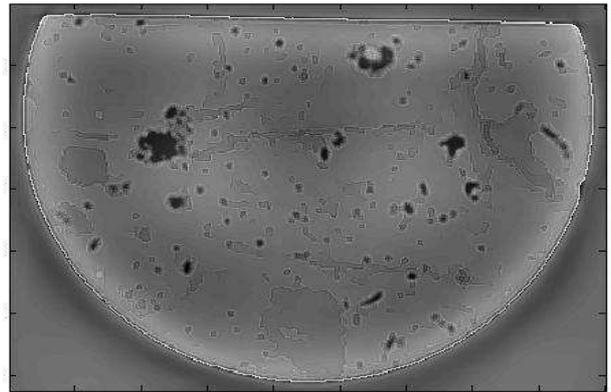


Figure 12: Image pre-processed after wavelet transform

Then a thresholding allows to keep only the vacuoles which are enhanced thanks to the wavelet transform.

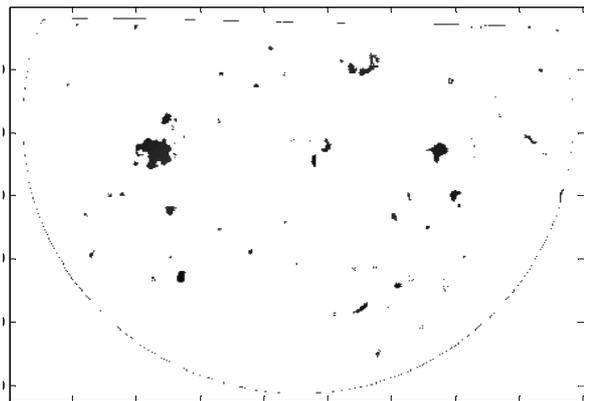


Figure 13: Image after thresholding

7.3. The curvelet transform

The curvelet transform is a tool for fault visualization. The curvelet transform is an effective tool to represent piecewise smooth images. It allows tracing sharp edges precisely, using a few elongated elements with very narrow widths.

The algorithm of the curvelet decomposition, using discrete curvelet transform, decomposes the image as a superposition of forms.

This method allows the transformation of the pre processed image as shown below:

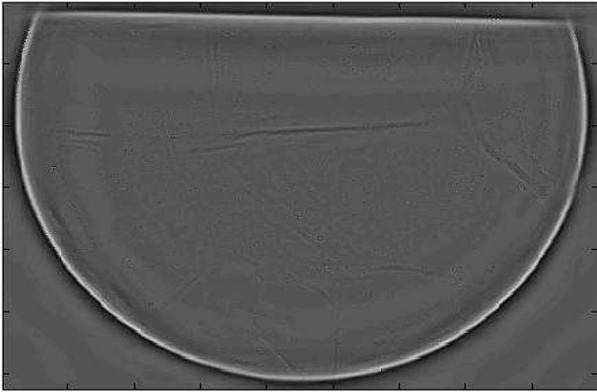


Figure 14: Image pre-processed after curvelet transform.

8. RESULTS

A comparative analysis of the different methods studied is recapped in the following table:

	Vacuoles detection	Exploitable vacuoles	Faults detection	Exploitable faults	Matlab program rapidity
Tensor structure	✓	✗	✗	✗	✓
Mathematic morphology	✓	✓	✗	✗	✓
MCALab library	✓	✓	✓	✗	✗

Table 1: Report

According to the previous studies, the processing line can be established. The chosen methods are different for vacuole and fault processes.

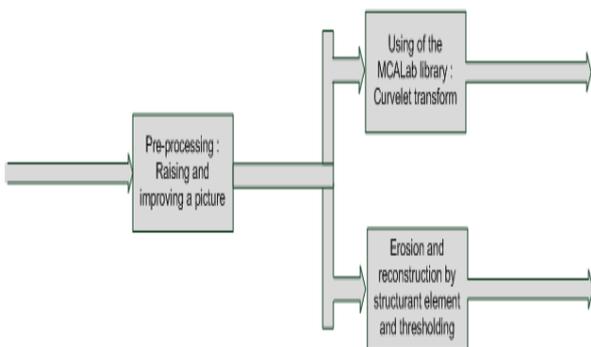


Figure 15: Processing line

8.1. Vacuole analysis

The mathematical morphology and erosion technique studies lead to binary pictures so that the contrast between the vacuoles and the rock is maximal.

From each of those images, a computing program has been developed in order to extract numerical result such as vacuole number and their area. Those results are usable for oil volume estimation

Example of numerical data obtained from the previous image:

Total surface area = **2993** pixels
 Higher vacuoles = **1155** pixels
 Meaning surface = **110.8** pixels
 Number of elements = **26**

8.2. Fault analysis

The decomposition by curvelet transform is the method selected for fault extraction.

However this method is too slow to be applied to the whole block of images (more than one hour for one image). Moreover, the faults are not contrasted enough to be properly detected. That is why numerical information cannot be obtained about the fault structures.

9. CONCLUSION

In this paper, a tomographic image chain process has been developed. This process aims at extracting two elements: vacuoles and faults in order to estimate the oil volume. The method excluded is the structure tensor one because of unusable results. Erosion technique is the most adapted for vacuole detection. This method is faster than wavelet transform one and results in a better visibility. That leads to numerical results such as vacuole number and total vacuole area of the image. Curvelet transform is the only method efficient for fault extraction but too slow to be used on the whole volume.

The pre-processing phase consisting in reducing noise and raising the contrast by mean of Anisotropic and Laplacian filter is the same for vacuole and fault detection.

Interface graphical user has been created in order to apply the line process on 2D and 3D tomographic pictures.

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