PORE-SCALE VISUALIZATION ON POLYMER FLOODING: APPLICATION OF SINGULAR VALUE DECOMPOSITION-BASED IMAGE ANALYSIS METHOD

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Through years of working with visualization studies on micromodels and Hele-Shaw cells, we have always been confronted with difficulties such as numerous images of long flooding processes to be analyzed, irregularities of laser-etched micromodels that complicate the analysis of pore images, poor lighting, and so on. Finally, we aimed to customize a simple method addressing our difficulties. The method is based on singular value decomposition coupled with contour tracing and is developed using the MATLAB programming language. It is built with an approach that allows easy application of the experience of an expert when it is needed. Singular value decomposition (SVD) has been utilized because of its attractive properties that are useful to our objectives, including image compression and image denoising. The method is experimented on pore-scale visualization of polymer flooding in a micromodel, and it showed a reliable performance. In this paper, the pore-scale analysis is chosen rather than calculating the overall oil recovery factor because it has more details to investigate and helps better to evaluate the performance of the proposed method. We calculated the residual oil and connate water saturation as a case study. The method’s unique procedure and features are explained step by step through the case study. The method facilitates the analysis by reducing the calculation time and the required storage space. Also, it offers an interesting component to decrease redundancies due to lighting problems.

KEY WORDS: image analysis, singular value decomposition (SVD), contour tracing, pore-level visualization, polymer flooding, wettability, connate water

1. INTRODUCTION

Image-based analysis methods are essential in vast areas of petroleum engineering, especially the visualization experiments (Heidaryan, 2019). Yeates et al. (2019) presented direct observation of foam flow through a 2D porous microfluidic device. Through a specially designed image analysis workflow including pre-processing and binarization, they performed individual bubble tracking and established flow dynamics within the micromodel structure. Liu et al. (2019) conducted an intensive study on the pore structures of a formation from North Dakota applying scanning electron microscope (SEM) image analysis. Xu et al. (2017) visualized the imbibition in the new two-and-
a-half-dimensional (2.5D) reservoir micromodel through water flooding experiments in water-wet and oil-wet 2.5D mediums. To process the images, the binarization method was used twice to divide oil, displacement fluids, and rock skeleton from the recorded images. Etemad et al. (2017) aimed to model the steam injection process and examine the displacement physics at the grain level. Through study, the micromodel images were binarized using ImageJ. A paper by Berrezueta and Kovacs (2017) demonstrates the application of an automated image processing method based on binarization for detection and analysis of pores in thin section petrographic microscopy (optical porosity). In a work by Yun and Kovscek (2015) etched silicon micromodels with well-characterized pore networks were used during single-phase flow to examine the retention of partially hydrolyzed polyacrylamide (HPAM) solution. Image analysis included an image subtraction and a red, green and blue (RGB)-based global thresholding technique for quantification of polymer retention/adsorption.

As mentioned, different methods have been developed and have been used case by case. However, we decided to develop a method learning from our experiences to better address our common issues through image processing of micromodel and Hele-Shaw cell visualizations. The method is built based on singular value decomposition. Singular value decomposition (SVD) has emerged as a promising paradigm for image processing and image-based analysis (Sadek, 2012). SVD has many attractive properties to offer, as in image compression (Bryt and Elad, 2008; Ranade et al., 2007), image denoising (Dhannawat and Patankar, 2016; Malini and Moni, 2015), watermarking (Chandra, 2002; Jia, 2014), and so on. Beneš and Kruis (2018) described application of SVD to the compression of results from finite-element solvers. Ye et al. (2016) performed a numerical study of heat source reconstruction for the advection-diffusion operator using a conjugate gradient method stabilized with SVD.

In this method the contour tracing also is coupled with the SVD to extract the accurate boundaries. The method helps to reduce the required memory space and calculation time. Also, it offers an interesting facet to decrease the noisy elements of images. We do not claim that other methods are not useful, but in parallel this is a simple customized method with new advantages for our necessities.

Polymer flooding in a glass micromodel was picked out as the case study to evaluate the method, since we have the necessary experience on it. At first, some experimental investigations at pore-level on wettability and connate water’s effect on polymer flooding efficiency is exhibited. Then, the proposed image processing method is described in detail. And finally, the method is applied on the obtained visualization results to calculate the residual oil and connate water saturations.

2. PORE SCALE VISUALIZATION

Micromodels are transparent artificial models of porous media that are used to simulate and discover transport mechanisms at the pore scale (Wilson, 1994; Nazari et al., 2019; Sarafraz et al., 2019).

They have been increasingly used in various research areas such as chemical flooding processes including polymer (Abedi et al., 2012), surfactant-enhanced water (Jamaloei and Kharrat, 2012), alkaline (Dong et al., 2012), alkaline-surfactant-polymer (Fu et al., 2016), emulsion (Karambeigi et al., 2015), biological like microbial enhanced oil recovery (Armstrong and Wildenschild, 2012; Soudmand-Asli et al., 2007), and other applications such as asphaltene precipitation (Doryani et al., 2016), hydrate formation (Hauge et al., 2016), and nanofluids in porous media (Khanaf and Vafai, 2019; Maleki et al., 2019a,b; Nojoomizadeh and Karimipour, 2016), and so on.

As mentioned, the case study investigates the effects of wettability and connate water saturation on the oil recovery factor of polymer flooding. In this section, some descriptions about the case are included. More about the experimentation, micromodel setup and its characteristics, test fluids, and other elements are given in detail elsewhere (Abedi and Kharrat, 2016; Abedi et al., 2012).

2.1 Wettability

Starting with macroscopic view, Fig. 1 shows polymer (in white) invading the saturated micromodel with crude oil (in black) at different wetting conditions. As illustrated, the displacement front in a water-wet medium is more stable than in an oil-wet medium. So it is expected that polymer flooding in a water-wet medium results in a higher oil recovery factor (Sadeghi et al., 2018; Hopp-Hirschler et al., 2019).
Figure 2 is a digital microscope image that illustrates (at the pore level, for oil-wet condition) the connate water phase in the form of individual droplets surrounded by continuous oil phase alongside isolated polymer solution. It confirms the instability at the polymer front (interface) for the oil-wet condition.

In a water-wet condition, relatively thick connate water film is formed along pore walls as water tends to spread on the grain surface (Fig. 3). It is observed that the film of oil phase was left unswept between the polymer solution and connate water film. Part of this is due to polymer solution breaking into connate water layer—the occurrence of snap-off. Also, the wetting alteration from strongly to moderately water-wet because of asphaltene precipitation is likely responsible for unswept oil films. But the polymer solution is continuous, the front is more stable, and the swept area is larger.

2.2 Connate Water

Moreover, Fig. 4(a) displays polymer solution breaking into connate water film and leaving oil unswept and trapped. It is deduced that the polymer solution got mixed up with a portion of connate water and its viscosity got degraded...
because of the brine quantity. Due to this phenomenon alongside snap-off trapping, the residual oil in place increases and affects the overall polymer flooding performance. Figure 4(b) provides zoomed-in visualization of the phenomenon in another pore throat.

In an oil-wet medium, the role of connate water is less influential (see Fig. 5). The trapping that happens here is pore-doublet model.

3. SINGULAR VALUE DECOMPOSITION (SVD)

Each image was read and converted to RGB and then to a grayscale one. Because a digitized image consists of pixels of say $m$ rows and $n$ columns, it is nothing but an $m \times n$ matrix (Sadek, 2012; Heath, 2002). Next, the matrix decomposition was applied.

The singular value decomposition of a matrix $A$ is the factorization of $A$ into the product of three matrices. Let $A$ be an $m \times n$ matrix with $m \geq n$. Then one form of the singular value decomposition of $A$ is

$$ A = U \Sigma V^T $$

where $U$ and $V$ are orthogonal and $\Sigma$ is a square diagonal. Where $U$ is $m \times \text{rank}(A)$, $V$ is $n \times \text{rank}(A)$, $UU^T = I_m$, $VV^T = I_n$ and

FIG. 5: Pore throat image of oil-wet medium—trapped crude oil in contact with polymer solution
is a \( \text{rank}(A) \times \text{rank}(A) \) diagonal matrix. The \( \sigma_i \)'s are called the singular values of \( A \) and their number is equal to the rank of \( A \) (Davis and Uhl, 1999; Alkiviadis and Malaschonok, 2004).

Also, \( \sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_{\text{rank}(A)} > 0 \). Considering \( p = \min(m, n) \) then \( \text{rank}(A) = k \) as \( k \leq p \), which indicates the number of singular value terms. The columns of \( U \) are called the left singular vectors of \( A \), and the columns of \( V \) are called the right singular vectors of \( A \) (Ganic et al., 2003).

The SVD is an efficient method to split the image into a set of linearly independent components, each of them bearing its own energy contribution. The SVD can offer low-rank approximation, which could be optimal subrank approximations by considering the largest singular value that pack most of the energy contained in the image (Andrews and Patterson, 1976; Sadek, 2012).

This property is highly advantageous for analysis based on images as shown in the following subsections.

### 3.1 Image Compression

Reduced SVD provides substantial memory savings over the original matrix while preserving most of the energy (information); by approximating the matrix with optimal rank \( A_k \) instead of the whole matrix \( A \) (Sadek, 2012; Kakarala and Ogunbona, 2001; Yang and Lu, 1995).

### 3.2 Image Denoising

Because singular values preserve the information of a digital image, the greater the singular values are, the more important the corresponding singular vectors are in representing the matrix \( A \). The lower singular values do not possess critical information and generally conserve noise energy. Hence, with applying low-rank approximation the effect of unwanted components could be minimized (Reddy and Aggarwal, 2015; Konstantinides et al., 1997).

To reach a more tangible understanding of the aforesaid properties, low-rank approximations were applied to the microscopic image of pore throat [Fig. 4(b)] and illustrated in Fig. 6.

As shown, with rank truncation the microimage loses some details but preserves the important ones. For example, there is a tiny difference between Fig. 6(d) with 50 terms of singular values and Fig. 6(e) maintaining six times more terms.

Figure 7 displays the relation between rank truncation, memory compression, and relative error comparing to the original microimage in an illustrative manner, here \( \text{Relative error} = \frac{\sigma_{k+1}}{\sigma_k} \) and \( \text{Memory storage } \% = \frac{k(m+n+1)}{(mn)} \).

The less singular value terms used, the less information, but important ones are maintained and so the less memory space needed. As a case, this glass model has 784 pores and more than 3,000 throats and there are thousands of microscopic images to be analyzed; this emphasizes how the aforesaid feature is important for facilitating the image processing.

This part was only an opening. Through next section the application of the developed method is investigated comprehensively.

### 4. METHOD APPLICATION

As an instance, the objective is to measure the residual oil in place of Fig. 4.

Contour tracing is a technique that is applied to the pore image to extract the boundaries. Contour tracing draws isolines of a matrix. Figure 8 shows all contours of this pore image. At the next step, the related contours are chosen to separate the area of residual oil in the pore.
FIG. 6: Low-rank approximations (a) $k = 1$; (b) $k = 10$; (c) $k = 20$; (d) $k = 50$; (e) $k = 300$; and (f) original ($k = 480$)

FIG. 7: Relative error and memory compression after rank truncation
FIG. 8: Contour lines of the pore image

But before that, SVD low-rank approximations were applied. Figure 9 displays approximated contour plots of the original one. Besides the aforesaid memory saving, Fig. 10 reveals a decrease in calculation time with less singular value terms used, which is another critical characteristic for image analysis (relative calculation time is inserted regarding the maximum rank).

Next, the contour lines to encompass the residual oil area were selected. Figure 11 shows the selected residual oil area at \( k = 10 \); the binarized image is inserted to do the comparison. It shows that \( k = 10 \) provides every detail needed to calculate the residual oil area (the lowest number of singular value terms that maintains our required details) and there is no need for more elements, which cost more space and time. In this procedure, the contour selection and low-rank approximation are somehow similar to the thresholding in the binarization method; an expert performs it regarding the objectives of analysis.

In this method, numbers of nearby contours could be selected to obtain the best averaged value for the area; this is really helpful. As another example, the connate water saturation in a specific pore (see Fig. 12) is requested. This case is more complicated because of the presence of a water layer at the pore edges. Figure 13 exhibits the interface contours between oil, water, and glass (using the same procedure explained through Figs. 6–11). As a great feature of this customized method, the appropriate counters for the desired area can be chosen on the image, and in this way the authors’ expertise could be applied in the best way possible.

To calculate the actual connate water saturation, in Area 1, the contour is selected in the middle of contact region between oil and water because here we got water with some oil residues on the glass, so the area is divided between oil and water saturation. Area 2 is not etched perfectly (especially at the edges, which do not contribute to the pore volume), consequently we only add half of this area to the total crude oil area. Areas 3 and 4 contain only connate water. In another approach, each area could be calculated separately using different contours and low-rank approximations. Based on the cases and the expert’s target, others may choose different counters to limit the desired area. But in general, the procedure is the same and it can be applied to any similar case (see supplementary section).

Next, as illustrated, there are some noisy elements in the contours due to poor lighting and shadows in the microimage. These noisy elements cause errors in calculations and should be eliminated as much as possible. Several low-rank approximations were employed. Truncating smaller singular value terms and their noisy details was continued till \( k = 17 \) offered the best part of the original energy needed to select the interface contours (see Fig. 14). In this way the contour lines also were smoothed, which makes it more feasible to calculate the area between them. As mentioned before, also the calculation time and the memory space required is reduced. Finally, the connate water saturation was measured from these areas as 18% (this value is 18.04% for \( k = 300 \)).

In Fig. 15, the connate water area as selected previously (limited to the dashed contour lines) is illustrated to be compared with the area separated by binarization method (in black). The binarization was repeated using two different threshold values. The comparison shows that the borders we selected are smoother, which improves the accuracy.
5. SUPPLEMENTARY SECTION

This part is inserted to explain the procedure in a clearer manner. The preceding case was chosen to demonstrate all the facets of the customized method—to show how those facets can be utilized. There are some tools available, so depending on what the experts are looking for they can be utilized; if the case is simpler, the simpler procedure is taken. As a simpler case, the method is utilized to investigate the viscous fingering in polymer flooding in a rectangular Hele-Shaw cell saturated with a mineral oil. In this procedure, since there is no problem of poor lighting, the single counter line is selected on one random image (similar to thresholding for binarization) and then best low-rank approximation only to economize time and memory, now all is fixed and is applied to the thousands of frames extracted from flooding video (see Fig. 16). The finger propagation by counter lines is also generated, which helps better to study the instability issue. Therefore, in each case depending on the existing objectives and concerns, the tools can be utilized: it could be single or multiple counter lines, using low-rank approximation to decrease redundancies or to economize your time and so on.

FIG. 9: Low-rank approximations: (a) $k = 1$; (b) $k = 2$; (c) $k = 5$; (d) $k = 10$; (e) $k = 50$; and (f) $k = 480$
FIG. 10: Relative calculation time vs. singular value terms used

FIG. 11: (a) Residual oil boundary contours (only 10 singular value terms maintained); and (b) binarized residual oil area

FIG. 12: Original image of a pore saturated with crude oil in presence of connate water
6. CONCLUSIONS

The proposed method was tested through polymer flooding in a five-spot glass micromodel. We calculated the residual oil and connate water saturations in a pore, and the results were compared with the binarization method. Besides being time and memory efficient, in many cases with image complexities such as poor lighting and redundant details, this method is promising. The insight of an expert who runs the tests can be employed better in this method, which brings great advantages. Considering the described procedure, it can be employed for various fluid transport processes in different transparent media, at both micro- and macroscale. To sum it up, the developed SVD-based method proved to be a practical tool in the challenging area of concern.
FIG. 15: Binarized area of connate water [with two different thresholding values a) 13.64% and b) 16.48%] vs. the area within smoothed boundary lines (dashed) selected with the method (from Fig. 14)

FIG. 16: Polymer flooding in a rectangular Hele-Shaw cell saturated with mineral oil—fingers propagation

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