Image Segmentation for Quantification of Air-Water Interface in Micro-CT Soil Images

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IMAGE SEGMENTATION FOR QUANTIFICATION OF AIR-WATER INTERFACE
IN MICRO-CT SOIL IMAGES

By

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Bachelor of Technology in Electronics and Communication Engineering
Jawaharlal Nehru Technological University, India
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ABSTRACT

IMAGE SEGMENTATION FOR QUANTIFICATION OF AIR-WATER INTERFACE IN MICRO-CT SOIL IMAGES

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Soils are complex environments comprising various biological (roots, water, air etc) and physical constituents (minerals, aggregates, etc). Synchrotron radiation based X-ray microtomography (XMT) is widely used in extracting qualitative and quantitative information regarding spatial distribution of biological and physical soil constituents. Segmentation of these micro-CT soil images is of interest to geologists, hydrologists, civil and petroleum engineers and soil scientists. In this present work, we study and implement segmentation algorithms for microhydrology studies, specifically for soil water conductivity. Three well-known image segmentation algorithms are studied for evaluating their performance for the task. We demonstrate the problems and ways to segment XMT images and extract data for evaluating the air pressure in the soil pores to promote soil hydrology studies. To this end we take the recommended in the literature approach to differentiate textures and segment images using Fuzzy C-means Clustering (FCM). Secondly, we demonstrate the performance of two state-of-the-art level-set based
active contours methods followed by curve fitting for radii detection and air pressure calculation.
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CHAPTER 1
INTRODUCTION

Soil is a heterogeneous mixture of various physical and biological constituents. Scientific groups of geologists, hydrologists, civil and petroleum engineers and soil scientists are especially interested in the identifying and classifying the different constituents present therein for various further studies. In recent years, image processing has become an important part for investigations on porous media (such as soil). Synchrotron X-rays, and thermal neutrons computed tomography are two prominent imaging techniques that are gaining popularity especially in the application with soil aggregates. X-ray Computed Tomography (XRT) imaging technique is among the widely popular way of obtaining high resolution images of porous media.

Image segmentation is an important step in the process of image analysis. Segmentation is the process of partitioning an image into a set of distinct regions, which are different in some important qualitative or quantitative way. Many researchers all over the world have explored the different image segmentation techniques on soil images [1–4].

This thesis study is incorporated under four major chapter divisions - Chapter 2 discusses details of the X-ray Microtomography imaging technique. The high resolution soil images are generated using this technique and are further analyzed using image segmentation techniques. In Chapter 3, the image segmentation algorithms used in the study are discussed. Three prominent algorithms are described namely, Fuzzy C-means Clustering (FCM) algorithm and two level-set based active contours segmentation techniques: Chan-Vese’s algorithm [5] and Shawn Lankton’s [6] localized region based
segmentation algorithm. The segmentation output generated through the application of these algorithms to micro-CT soil images is discussed in the results section of Chapter 4. Conclusions are drawn and best results are further quantified by fitting curves and calculating radii of air blob at the air-water interfaces. These radii are used by scientists for evaluating the air pressure in the soil pores to promote soil hydrology studies. The equation is provided. Finally, the ramifications of the study are concluded in Chapter 5 with some suggestions on improvement to the present work.
CHAPTER 2

X-RAY MICRO-TOMOGRAPHY (XMT) IMAGING

Computerized tomography is a non-destructive and non-invasive imaging technique. The basic principles of computerized tomography were presented by Kak and Slaney [7]. X-ray imaging is essentially based on difference in attenuation of X-rays. A primary X-ray beam focused on an object interacts with constituents of the object causing absorption and scattering of the primary X-ray. Thus, the intensity of the transmitted X-ray beam ($I$) is lesser than the intensity of the incident beam ($I_0$). The reduction in the intensity is governed by the Lambert-Beer’s law which is expressed as shown in Eq. 2-1 [8].

$$I = I_0 \exp(-\mu x)$$  \hspace{1cm} \text{Eq. 2-1}

Where,

$\mu$= overall linear attenuation coefficient (The ratio between the scattered and the transmitted photons is known as the attenuation coefficient)

$x$=sample thickness

At longer wavelengths (i.e. lower energies $< 100-150$ keV) of the X-rays, photoelectric absorption dominates. Whereas, at shorter wavelengths (i.e. higher energies $>150$ keV), density controlled Compton scattering dominates.

When a porous media of various phases (solid, liquid or gaseous; viz. soil) is involved, the Lambert-Beer’s law is modified to include specific attenuation coefficients. This can be expressed as shown in Eq. 2-2 [8].
\[ I = I_0 \exp\left[-\left((1 - \theta_p)\mu_s \rho_s x + \theta_p S_w \mu_w \rho_w x\right)\right] \quad \text{Eq. 2-2} \]

Where,
\[
\begin{align*}
\rho_s \text{ and } \rho_w & = \text{densities of solid phase and liquid phase} \\
\mu_s \text{ and } \mu_w & = \text{linear attenuation coefficients of solid phase and liquid phase} \\
S_w & = \text{water saturation} \\
\theta_p & = \text{total porosity} \\
x & = \text{sample thickness}
\end{align*}
\]

Note that in the above equation, the linear attenuation of gaseous phase is neglected as it is comparably small.

### 2.1. Image acquisition

The experimental arrangement for a typical image acquisition process through synchrotron X-ray attenuation micro-tomography is shown in Figure 2.1. The essential components involved in image acquisition process include X-ray source (point source or synchrotron), double-crystal monochromator, detector camera system, sample orientation manipulator and sample to be scanned.

Different XMT facilities across the world use beams with different characteristics (geometry of the beam, energy etc). Some scanners use a planar fan beam or a cone beam, whereas a synchrotron source uses a parallel beam (see Figure 2.2), which is used at the experimental facility at Lawrence Berkeley National Laboratories (LBNL). We used the XMT facility at Advanced Light Source, LBNL, California using variety of
plants grown in different porous media. The size of the container used was 1 cm in
diameter in most of our experiments and resolution was ~5 µm.

Synchrotron radiation is a part of electromagnetic radiation spectrum that is emitted when
ultra-high-speed charged electrons interact with a magnetic field [9]. The detector is
typically a high-resolution CCD camera. Images can be acquired via radiography (2D) or
tomography (3D). A large number of these 2D projections are needed to obtain a 3D
spatially-distributed map of attenuation; this is achieved by imaging the sample in small
angular steps (viz. 0.2°) from 0° to 180°. This stack of images is then reconstructed to
produce a 3D image.

The resolution of the image is obtained by dividing the number of pixels (N) on the
detector and the sample size (D). For example, if the number of pixels on the detector is
2000, and the sample is 1000µm in diameter, the maximum resolution that can be
achieved is 2 µm. However, for a cone beam source, this may vary depending on the
position of sample between the source and the detector.

Figure 2.1. Typical schematic of X-ray microtomography experimental setup [10]
Figure 2.2. Various X-ray beam configurations [11]
The soil images obtained through XMT technique at LBNL are a stack of high resolution (4000 × 4000) images. Figure 2.3 shows a sample of soil image comprising water, air and aggregates.

Figure 2.3. Image of a micro-CT scan of partially saturated clay aggregates without root (pixel size - 2.2 microns).
CHAPTER 3

IMAGE SEGMENTATION TECHNIQUES

The already existing research in the field of image segmentation of heterogeneous soil images primarily used binary classification through various thresholding techniques such as Huang, Intermodes, IsoData, Li, MaxEntropy, Mean, MinError(I), Minimum, Moments, Otsu, Iterative thresholding, RenyiEntropy, Shanbhag, Triangle, Yen methods [12–23]. These techniques are barely able to classify the soil images into two classes. Substantial work on implementation of these methods to soil images has been carried out by prior researchers [24] [25]. All aggregates are categorized under one classification while all the pores (air, water) are categorized under another classification. For the task of quantification of air-water interface, there is a need for classification of soil image into more than two classes. Thus, in order to achieve this task, three prominent advanced image segmentation algorithms namely: Fuzzy C-means (FCM), Chan-Vese’s multiphase active contours and Shawn-Lankton’s localized region based segmentation are used in this study. The following sections will discuss them in further detail.

3.1. Fuzzy C-Means (FCM) algorithm

The Fuzzy C-Means (FCM) is an unsupervised clustering method which is used to classify a set of data into two or more clusters. This algorithm was first developed by Dunn in 1973 [26] and further refined by Bezdek in 1981 [27]. Since then it has been one of the widely used algorithms for pattern recognition. It has been successfully applied to problems in several fields such as astronomy, chemistry, geology, image analysis, medical diagnosis, shape analysis, target recognition etc that involves feature analysis,
clustering, classifier design and image segmentation. The main advantages of this method are its straightforward implementation, applicability to multichannel data, fairly robust behavior and the ability of uncertainty data modeling. But, the major disadvantage of the use of the FCM algorithm in imaging applications is that it does not incorporate spatial context information, causing it to be sensitive to noise and other imaging artifacts. The Fuzzy C-means algorithm is used to cluster the obtained feature vectors [28] into several classes corresponding to the different regions of the multi-textured image. The data set is subjected to a fuzzy partition. For the partition of a data set \( x = [x_1, x_2, \ldots, x_d]^T \), the FCM algorithm tries to minimize the objective function \( J_m \) given by Eq. 3-1 [29]

\[
J_m(u, v) = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{i,k}^m \|x_k - v_i\|^2
\]

Eq. 3-1

In this Eq. 3-1, ‘\( d \)’ is the number of samples in the vector \( x \), ‘\( c \)’ is the number of clusters \((1 \leq c \leq d)\), \( u_{i,k} \) is the element of the partition matrix \( U \) of size \((c \times d)\) containing the membership function, \( m \) is a weighting factor that controls the fuzziness of the membership function and is any real number greater than 1 and \( v_i \) is the center of the \( i^{th} \) cluster. The matrix \( U \) is constrained to contain elements in the range \([0,1]\) such that \( \sum_{i=1}^{c} u_{i,k} = 1 \) for each \((1 \leq k \leq d)\), \( u_{i,k} \). The norm \( \|x_k - v_i\| \) is the distance between the sample \( x_k \) and the centers of classes \( v_i \). For segmentation of a multi-textured image of size \((N \times M)\), the vector \( x \) contains all the gray level of the image, scanned line by line, i.e. \( d = NM \). The FCM algorithm performs the partition of the vector \( x \) into \( c \) fuzzy subsets where \( u_{i,k} \) represents the membership of \( x_k \) in class \( i \).
3.1.1. FCM using statistical features

A cascade clustering method combining statistical features and the standard Fuzzy C-means clustering algorithm is used for segmentation of soil images in the present work. In this method, the feature vector $\mathbf{x}$ used for the image segmentation based on the pixel value in the FCM algorithm is replaced by a matrix $\mathbf{F}$ containing the same number of rows, i.e. $d$, but with 4 columns.

For a textured image $\mathbf{y}$ of size $(N\times M)$, and a sliding window of size $(P\times P)$, the 4 features—mean (Me), Variance, $3^{rd}$ order moment and $4^{th}$ order moment are extracted from the window centered at pixel $(n, r)$ by using the following equations (Eq. 3-2 to Eq. 3-5) [29].

$$Me = \frac{1}{P^2} \sum_{i=\frac{P-1}{2}}^{\frac{P-1}{2}} \sum_{j=\frac{P-1}{2}}^{\frac{P-1}{2}} \mathbf{y}(n+i, r+j) \quad \text{Eq. 3-2}$$

$$Variance = \frac{1}{P^2} \sum_{i=\frac{P-1}{2}}^{\frac{P-1}{2}} \sum_{j=\frac{P-1}{2}}^{\frac{P-1}{2}} (\mathbf{y}(n+i, r+j) - Me)^2 \quad \text{Eq. 3-3}$$

$$3^{rd} \text{ Order Moment} = \frac{1}{P^2} \sum_{i=\frac{P-1}{2}}^{\frac{P-1}{2}} \sum_{j=\frac{P-1}{2}}^{\frac{P-1}{2}} (\mathbf{y}(n+i, r+j) - Me)^3 \quad \text{Eq. 3-4}$$

$$4^{th} \text{ Order Moment} = \frac{1}{P^2} \sum_{i=\frac{P-1}{2}}^{\frac{P-1}{2}} \sum_{j=\frac{P-1}{2}}^{\frac{P-1}{2}} (\mathbf{y}(n+i, r+j) - Me)^4 \quad \text{Eq. 3-5}$$
To obtain a centered window around each pixel, ‘P’ must have an odd value. The FCM algorithm is used to cluster the obtained feature matrix $F$ into $c$ different classes, where each class corresponds to one region in the segmented image. Figure 3.1 shows the spatial scanning order of an image performed, pixel by pixel from left to right and top to bottom.

![Image](image.png)

Figure 3.1. The adaptive sliding window to calculate features of an image from left to right and top to bottom [29].

The image segmentation technique using the FCM algorithm combined with the statistical features can be summarized by the following steps [29]:

**Step 1:** Initialization (Iteration $t=0$)

Randomly initialize the matrix $V^{(0)}$ of size $(c \times 4)$ containing the centers of the classes.

**Step 2:** Construction of the matrix $F$ of size $(d \times 4)$ containing the statistical features extracted from the textured image as detailed in the last paragraph.

From the iteration $t = 1$ to the end of the algorithm:

**Step 3:** Calculate the membership matrix $U^{(t)}$ of element $u_{ik}$ using Eq. 3-6.
\[ u_{ik} = \left( \sum_{j=1}^{c} \left( \frac{\| F_k - v_i \|}{\| F_k - v_j \|} \right)^{2/m-1} \right)^{-1} \]  
\text{Eq. 3-6}

Here, \( F_k \) and \( v_i \) are vectors of size \((1 \times 4)\).

**Step 4:** Calculate the matrix \( V(\tau) \) composed of 4 columns \( v_i \) using:

\[ v_i = \frac{\sum_{k=1}^{d} u_{ik} m F_k}{\sum_{k=1}^{d} u_{ik} m} \]  
\text{Eq. 3-7}

**Step 5:** Convergence test: if \( ||V(\tau) - V(\tau-1)|| > \varepsilon \), then increment the iteration \( \tau \), and return to the **Step 3**, otherwise, stop the algorithm. \( \varepsilon \) is a chosen positive threshold.

### 3.2. Active contour techniques

Active contour segmentation techniques have become very popular in recent years, and have found wide range of applicability in problems pertaining to visual tracking and image segmentation [30], [31]. The basic idea is to allow a contour to deform so as to minimize a given energy functional in order to produce the desired segmentation, i.e. the curve or contour is fitted iteratively to an image based on its shape and the image values until it stabilizes (ideally on an object’s boundary). Based on the shape of the curve, the active contours can be classified into two types; parametric active contours and geometric active contours. In parametric active contours, the curve will be a polygon which is stored in terms of vertices and each vertex is moved iteratively. While the geometric active contour is a continuous curve stored in terms of coefficients. The curve is sampled into numerous finite divisions and the samples are moved iteratively. In each iteration, the new coefficients are evaluated for the evolved contour.
3.2.1. Chan-Vese active contour algorithm

Chan-Vese’s multiphase active contour algorithm extends and generalizes the active contour model without edges based binary segmentation and level sets, previously proposed by the authors in [32]. In that previous work, the basic idea to obtain an active contour model for object detection was to look for a particular partition of a given image into two regions, one representing the objects to be detected or foreground, and the second one representing the background [5]. The active contour was given by the boundary connecting these two regions. The model obtained was a particular case of the minimal partition problem of Mumford and Shah (1989) [33] for segmenting images. The active contour model from Chan and Vese (1999, 2001) [32], the level set method of Osher and Sethian (1988) [34] was used, together with a particular numerical approximation, which allowed to detect interior contours automatically. The method was then easily extended to vector-valued images (Chan et al., 2000) [35], which is robust with respect to noise. In addition, this active contour model (based on binary segmentation), to segment images with more than two regions, is generalized by using a new multiphase level set framework for piecewise constant and piecewise smooth optimal approximations [5].

The Chan-Vese algorithm is a geometric active contour model. Here the initial segmentation is defined with a contour in the image plane and then the contour is evolved using some evolution equation. The objective is to evolve the contour in such a way that it stops on the boundaries of the foreground region. There are different ways to define the evolution equation; for instance, the contour might move with the image gradient at a
point or with a velocity that depends on the local curvature at that point. The contour in Chan-Vese’s algorithm evolves through a level set method.

### 3.2.1.1. Level Set Method

Level set method is a powerful tool for performing contour evolution. If we have a level-set function \( \Phi(i, j, t) \), where \((i, j)\) are coordinates in the image plane and \(t\) is an artificial “time”. The level set function defines an edge contour and a segmentation of the image simultaneously at any given time. The edge contour is taken to be the zero level set \( \{(i,j) \text{ s.t. } \Phi(i,j,t)= 0\} \), and the segmentation is given by the two regions \( \{\Phi \geq 0\} \) and \( \{\Phi \leq 0\} \). The level set function will be evolved according to some partial differential equation, and hopefully will reach a steady state \( \lim_{t \rightarrow \infty} \Phi \) that gives a useful segmentation of the image [36].

### 3.2.2. Localized Region Based Active Contour Segmentation

Localized region based active contour algorithm is a hybrid technique developed by Shawn Lankton et al. based on two well-known segmentation techniques—gradient-based active contours and region-based active contours [6], [37]. This is an active contour segmentation technique, i.e. a curve is deformed over time iteratively until an optimum segmentation is reached. It analyzes statistics in small local regions of an image to separate the object to be detected or foreground from the background.

Edge-based flows get edge information using an edge detector, and then try to fit a curve on those detected edges. Here the main problem is, these methods only look at very local image information, which means it depends a lot on the initial placement of the curve and
susceptible to noise [38]. While the region-based flows try to model the global characteristics of entire regions of the image. This approach is nice because it’s very robust to noise and initialization, but will not work for all images as they can’t be modeled well in terms of global rules and incorrect segmentations occur [32].

The hybrid flow tries to take the advantages of both geodesic active contours and region based active contours. By forming a cost based on a shortest weighted path this can be accomplished. The weights at each point along the path are determined from local regions around the curve. The resulting flow is more robust to image noise like region-based flows and initial curve placement, but also capable of finding significant local minima and segmenting the image without making global assumptions.

It is assumed that each point on the true edge of an object (to be segmented), close by points inside and outside the object will be modeled well by the mean intensities of the local regions. With this we get an energy that is more global in nature than gradient-based flows. The cost of the complete curve is often called energy. This hybrid energy is defined using several notations. ‘I’ represents the image, ‘s’ and ‘x’ represent independent spatial variables. Omega (Ω) and Omega-bar (Ω) represent the interior and exterior of the curve respectively. Chi (χ), represents a circle centered at the point ‘s’ that tells about the local region being examined.

The functions \( u_l \) and \( v_l \) are defined in terms of local areas \( A_{It}, A_{Et} \) and local sums \( S_{It}, S_{Et} \)

The following notations describe the model [6], [37]:

\[
u_l(s) = \frac{S_{It}(s)}{A_{It}(s)} \quad \text{Eq. 3-8}\]
\[ v_I(s) = \frac{S_{E_t}(s)}{A_{E_t}(s)} \]  
Eq. 3-9

\[ S_{I_t}(s) = \int_{x \in \Omega} I_X(x, s) \, dA \]  
Eq. 3-10

\[ S_{E_t}(s) = \int_{x \in \Omega} I_X(x, s) \, dA \]  
Eq. 3-11

\[ A_{I_t}(s) = \int_{x \in \Omega} \chi(x, s) \, dA \]  
Eq. 3-12

\[ A_{E_t}(s) = \int_{x \in \Omega} \chi(x, s) \, dA \]  
Eq. 3-13

Based on these notations, the hybrid energy is given as:

\[
E = \oint_{C(s)} \int_{x \in \Omega} (I_X(x, s) - u_I(s))^2 + \int_{x \in \Omega} (I_X(x, s) - v_I(s))^2 \, ds \]  
Eq. 3-14

In Eq. 3-14, an outer integral over \( s \) is used to cover the points along the curve \( C(s) \). Both the inner integrals are evaluated over \( x \) and are used to inspect the entire domain restricted by the Chi function. Thus the only contribution is from image information in the local neighborhood around the point \( s \). The energy in the vicinity of each point \( s \) is a function of how well the interior and exterior regions are modeled by their respective mean intensities \( u_I \) and \( v_I \). The overall energy is the sum of the contribution of energy from every point around the curve [37].

Applying the mathematical concepts in calculus of variations, we can obtain the derivative of the energy function \( E \) with respect to the shape of the curve \( C(s) \) itself. Thus, the curve is deformed iteratively such that this energy is always decreasing. The estimate is continuously refined until we finally converge at an optimum local minimum value.
CHAPTER 4

RESULTS AND DISCUSSION

The image segmentation algorithms discussed in the previous chapter are implemented on micro-CT soil images to obtain various results. This chapter discusses the results in detail.

4.1. FCM Results

The FCM algorithm is implemented using MATLAB. Figures 4.1. (a), 4.1. (b) show the original and segmented output using FCM clustering algorithm considering mean and 3rd moment vectors using 9×9 window.

![Figure 4.1. (a) Original Soil Image (b) Segmented output](image)

Here, presumably, without classifying formally: Root, Water – Blue; Air – White; Particles (hard components) – Red; Aggregates – Yellow.
4.1.1. FCM Results for different exponential factor (m)

Figures 4.2 – 4.6 show the segmentation results using FCM algorithm for different values of exponential factor (m = 2 to 10) with mean and 3rd moment feature vectors using 9×9 window.

Figure 4.2. (a) Original Soil Image (b) Segmented output, m = 2
Figure 4.3. (a) Segmented output, $m = 3$ (b) Segmented output, $m = 4$

Figure 4.4. (a) Segmented output, $m = 5$ (b) Segmented output, $m = 6$
Figure 4.5. (a) Segmented output, m = 7 (b) Segmented output, m = 8

Figure 4.6. (a) Segmented output, m = 9 (b) Segmented output, m = 10

As the exponential factor (m) is increased from 2 to 10, the quality of detecting segments increases; for m > 8 the water and air clusters are classified as one cluster and soft and hard aggregates as combined into one class.
4.1.2. FCM Results for different classes

Figure 4.7. (a) Original Soil Image (b) Segmented output, 3 classes

Figure 4.8. (a) Segmented output, 4 classes (b) Segmented output, 5 classes

It has been observed that the 4-classes selection gives the best classification for the method, yet not sufficient for quantification.
4.1.3. FCM Results using different feature calculation window sizes

Figure 4.9. (a) Original Soil Image (b) Segmented output using window $3 \times 3$

Figure 4.10. Segmented output (a) using window $5 \times 5$ (b) using window $7 \times 7$
Figure 4.11. Segmented output (a) using window $9 \times 9$ (b) using window $11 \times 11$

Figure 4.12. Segmented output (a) using window $13 \times 13$ (b) using window $33 \times 33$
4.1.4. FCM Results for different sizes of image

Figures 4.13 – Figure 4.18 show the original image and FCM segmented output for image sizes 64×64, 128×128, 256×256, 512×512, 700×700 and 1024×1024 with mean and third moment features calculated using 9×9 window.

Figure 4.13. SweetPea_0_64×64 (a) Original Soil Image (b) Segmented output

Figure 4.14. SweetPea_0_128×128 (a) Original Soil Image (b) Segmented output
Figure 4.15. SweetPea_0_256×256 (a) Original Soil Image (b) Segmented output

Figure 4.16. SweetPea_0_512×512 (a) Original Soil Image (b) Segmented output
Figure 4.17. SweetPea_0_700×700 (a) Original Soil Image (b) Segmented output

Figure 4.18. SweetPea_0_1024×1024 (a) Original Soil Image (b) Segmented output
4.1.5. FCM Results for different Images: Using Mean and 3\textsuperscript{rd} Moment Features

Figure 4.19. SweetPea_0 (a) Original Soil Image (b) Segmented output

Figure 4.20. SweetPea_28 (a) Original Soil Image (b) Segmented output
4.1.6. Summary of FCM results

As we have observed, the clustering using FCM is not accurate for delineation of air-water interface. Non-uniformity of intensity distribution across the high resolution image creates a biased in statistics and leads to errors. Increasing the window size leads to inaccuracy in calculating spatial location of the interface curve. These factors make the above described method infeasible for the application. In active contours method, we process reasonably small regions around the area of interest. This assumes human interaction, but as we will see in the next section would yield a better segmentation results, i.e. one suitable for quantitative analysis.
4.2. Chan-Vese Active contour segmentation results

In this section, the segmentation results obtained using Chan-Vese’s multiphase active contour algorithm for different air-water interface images are discussed. A segmentation result is sensitive to few parameters such as length term ($\mu$), initial contour (shape, size and region of interest), and number of iterations. It was found experimentally that $\mu$ is to be 0.08 and the number of iterations is to be set to 1000. These values are used for results in Figures 4.22-4.27, where the interface of interest is marked by an arrow. The user can, however, change the parameters if the result is not satisfactory. For example, in Figure 4.28 the best result is obtained for 2000 iterations.

Figure 4.22. Interface 1: sweet pea soil image, $\mu = 0.08$, 1st row: left-a region of interest, right-initialization of the curves; 2nd row: left-contours, right-segmented image
Figure 4.23. Interface 1: sweet pea soil image, $\mu = 0.1$, 1st row: left-a region of interest, right-initialization of the curves; 2nd row: left-contours, right-segmented image
Figure 4.24. Interface 2: sweet pea soil image, $\mu = 0.08$, 1st row: left-a region of interest, right-initialization of the curves; 2nd row: left-contours, right-segmented image
Figure 4.25. Interface 3: sweet pea soil image, $\mu = 0.08$, 1st row: left-a region of interest, right-initialization of the curves; 2nd row: left-contours, right-segmented image
Figure 4.26. Interface 4: sweet pea soil image, $\mu = 0.08$, 1st row: left-a region of interest, right-initialization of the curves; 2nd row: left-contours, right-segmented image
Figure 4.27. Interface 5: sweet pea soil image, $\mu = 0.08$, 1st row: left-a region of interest, right-initialization of the curves; 2nd row: left-contours, right-segmented image
Figure 4.28. Interface 6: sweet pea soil image, $\mu = 0.08$, 1st row: left-a region of interest, right-initialization of the curves; 2nd row: left-contours, right-segmented image

4.2.1. Summary of Chan-Vese’s multiphase active contour algorithm results

The method produces results tractable by visual analyzer. In most cases, the obtained contour is suitable for direct quantification (radii calculation). An imperfect contour is corrected using either thinning or curve fitting as will be discussed in a later section.
4.3. Localized Region based segmentation results

As mentioned earlier the localized region based segmentation technique combines the advantages of geodesic active contours and the region based active contours. The results (Figures 4.29 – 4.34) show that the air blob is segmented accurately. It can also be seen that the water area near the interface is segmented, but the contour near the interface is extended into the air blob region.

Figure 4.29. Interface 1: clay-water image, iterations = 3000, 1st row: left-a region of interest, right-initial contour; 2nd row: left- evolved contour, right- air segmented image
Figure 4.30. Interface 1: clay-water image, iterations = 3000, 1\textsuperscript{st} row: left-a region of interest, right-initial contour; 2\textsuperscript{nd} row: left- evolved contour, right- water segmented image

Figure 4.31. Interface 1: overlap of contours: red - water, blue - air
Figure 4.32. Interface 2: clay-water image, iterations = 3000, 1st row: left-a region of interest, right-initial contour; 2nd row: left- evolved contour, right- air segmented image

Figure 4.33. Interface 2: clay-water image, iterations = 3000, 1st row: left-a region of interest, right-initial contour; 2nd row: left- evolved contour, right- water segmented image
4.3.1. Summary of Localized Region based segmentation results

The limitation of the method is in its binary nature of operation, i.e. a foreground object is extracted. Overall, this leads to frequent situations like one shown in Figure 4.34 and extension of the interface line such as in Figure 4.33. Generally, the results obtained through localized region based segmentation are inferior to those produced by the Chan-Vese’s method described in Section 4.2. The latter is selected for further analysis and calculations.
4.4. Curve-fitting

It follows from previous sections (see 4.2) that Chan-Vese’s segmentation method can be used for the application. Although it needs human interactions, the most of operations are performed automatically except selection of the region. Furthermore, the number of iterations per regions can be selected based on the result. Because of the imperfect delineation of the curve, the next step comprises curve fitting. Curve fitting is the process of constructing a curve or a mathematical function that has the best fit to a series of data points. Polynomial regression which is very useful to create a standard curve for interpolation or to create a smooth curve has been used for curve fitting process. From the segmented image obtained through Chan-Vese’s active contour algorithm, an edge map is created and the air-water interface is extracted. Figures 4.35 – 4.37 explains the process. The interface curve is extracted by setting the end point coordinates.

Figure 4.35. Edge map for Interface 1: Sweetpea_0 using Chan-Vese’s algorithm with mu = 0.08 and iterations = 3000
Using curve fitting tool in MATLAB, a quadratic polynomial, \( f(x) = p_1 x^2 + p_2 x + p_3 \) is fit to the data points extracted from Figure 4.35. This process yields values of polynomial coefficients \( p_1=0.00303 \), \( p_2=-0.1116 \) and \( p_3=1.056 \) with 95% confidence bounds. The following Figure 4.37 shows a snapshot of MATLAB curve fitting operation.

![Curve fitting using quadratic polynomial](image)
4.5. Radius and Pressure Calculation

Mathematically, if a curve is of the form $y = f(x)$, then the radius of curvature ($R$) is determined by Eq. 4-1 [39]

$$R = \left[ 1 + \left( \frac{dy}{dx} \right)^2 \right]^{3/2}$$

Eq. 4-1

As seen in Eq. 4-2, in order to evaluate the radius of curvature ($R$), we require both the first order and second order derivatives of $f(x)$ with respect to $x$. Both those derivatives can be extracted using analysis section of the curve fit tool in MATLAB. This procedure (as shown in Figure 4.38) is applied to the polynomial fit, $f(x) = 0.00303 x^2 - 0.1116 x + 1.056$ obtained in the previous section.

![Figure 4.38. Snapshot of MATLAB window for evaluating the first and second order derivates of the curve at different points](image)

Figure 4.38. Snapshot of MATLAB window for evaluating the first and second order derivates of the curve at different points
Finally, the radius of curvature (R) is evaluated at 20 different data points on the curve using Eq. 4-2 are shown in Figure 4.39. The average radius of curvature (R) is 83.3113 pixels i.e. equal to 183.2849 microns (each pixel = 2.2 micron).

![MATLAB Window](image)

Figure 4.39. Snapshot of MATLAB window displaying radius of curvature at different points
The pressure exerted by air blob on water at the air-water interface is given by Eq. 4-2.

\[ P = \frac{4Y \cos \theta}{D} \]  \hspace{1cm} \text{Eq. 4-2}

Where \( Y \) is the surface tension of water \( (72 \times 10^{-3} \text{ N/m}) \), \( \theta \) is the contact angle and \( D = 2 \times \text{radius of curvature, R} \) is the pore diameter. Once, the contact angle \( (\theta) \) is obtained, the pressure \( (P) \) exerted can be easily evaluated.
CHAPTER 5

CONCLUSION AND FUTURE WORK

The micro-CT soil images are segmented using cutting-edge algorithms in image segmentation. The FCM algorithm was used to cluster the various constituents of the soil. The four constituents segmented using FCM algorithm are: air, water, soft and hard aggregates. Then, the two most prominent level-set based active contouring algorithms- Chan-Vese’s multiphase active contours and Shawn Lankton’s localized region based segmentation techniques are used to achieve the goal of segmenting the air-water interface. The air-water interface contour is extracted from the segmented output and curve fitting is performed by quadratic polynomial. The final output yields the radius of air blob at the air-water interface which is further used in evaluating the air pressure in the soil pores. The work is an effort in assisting scientist in the analyses of image data and automating quantification process.

This work is an improvement over the previously used binary classification, i.e. thresholding, which limits the analyses to soil compaction only. In future, this two-dimensional analysis can be enhanced further by using the third dimension (stack of slices).
REFERENCES


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