SEGMENTATION OF SOILSECTION IMAGES USING CONNECTED OPERATORS

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ABSTRACT

Segmentation of soilsection images is an important task for automating the measurement of the grains' properties as well as for detecting and recognizing objects in the soil, important for its bioecological quality. In this paper, we apply several types of morphological systems to watershed-based segmentation of soilsection images. We use efficient connected operators such as reconstruction open-closing and area open-closing as well as some relatively new operators, the levelings, for image denoising, simplification, and feature/marker extraction. Further, we introduce an improvement of the reconstruction operators used in segmentation, based on a generalized multiscale connectivity analysis.

1. INTRODUCTION

In automated soilsection image analysis, an important task is to detect elementary objects, e.g. grains or aggregates, and differentiate these soil formations from void space. Image segmentation is thus one of the most useful tools for partitioning the image into separated elementary regions and subsequently evaluating pertinent properties, such as shape, size or texture. This is however a complex problem that consists of: (a) denoising and image simplification, including filtering and edge enhancement depending on the application, (b) feature/marker extraction for detecting significant regions in an image, and (c) obtaining the exact area covered by each one of the marked regions, by applying a method such as the watershed transform.

In this paper, we apply several standard as well as some relatively new morphological systems to perform a watershed-based segmentation of soilsection sample images. We focus on the use of connected operators, such as reconstruction and area open/closings as well as levelings, for denoising, image simplification and marker extraction. Experimental results obtained from the application of these morphological segmentation methods for various soilsection image samples are presented in section 3. Although these images have a very complex structure, exhibiting a variety of geometric features, the obtained results are very satisfactory, which indicates the efficiency of the proposed methods, especially demonstrating the exact contour preservation property of connected operators. Section 4 proposes some improvements of the reconstruction operators based on the development of a theoretical framework for generalized multiscale connectivity analysis.

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2. BACKGROUND ON WATERSHED SEGMENTATION

Image segmentation is one of the most important and most difficult problems in the field of computer vision. Generally speaking, it is the process of isolating objects in the image from the background, i.e partitioning the image into disjoint regions, each one being homogeneous and connected with respect to some property, such as grey-value or texture. Since the term *homogeneous* is rather vague and allows many different interpretations of its meaning, the task of image segmentation appears to be problem-dependent. In the case of soilsection images, the segmentation proves to be a very difficult task due to the fact that the specific category of images has very low contrast, complex structure and often overlapping components.

A well-known segmentation methodology is the watershed approach [1], which is the preferred solution in the field of mathematical morphology. This task can be divided into three different stages: (a) preprocessing and image simplification, (b) region-feature extraction and (c) watershed transform. The objective of (a) is to reduce the presence of noise and make the image easier to segment by removing useless information, thus producing an image that consists mostly of flat and large regions. One family of filters, often used for image simplification, is the *alternating sequential filters (ASF)*, obtained by applying openings and closings alternately. At stage (b), the goal is to extract some special features from the simplified image such as small homogeneous regions, called markers, which will be used as the starting points for the flooding process. Their exact size and shape have no importance since they simply modify the local homogeneity by being imposed to the topographic relief as regional minima [1]. The selection of the markers is probably the most difficult task and the method used for their extraction depends on the desired results for each specific application. At stage (c), the watershed transform is applied on the morphological gradient of the simplified image. It can be viewed as the process of flooding a topographic surface using the markers as sources. The watershed construction grows the markers until the exact contours of the objects are found. An efficient way to implement it is via hierarchical queues, using an ordering relation in flooding [1].

3. SEGMENTATION OF SOIL IMAGES

Soil structure is concerned with the size, shape, and arrangement of primary particles and voids. Soilsection images exhibit a great variety of geometric features which can be either 1D, such as edges or curves, or 2D such as light or dark blobs (small homogeneous regions of uncertain shape, which sometimes seem to be randomly distorted circles or ellipses) providing useful information for the evaluation of soil structure quality. In order to detect and extract the objects of interest (i.e soil particles and grains) soilsection images need to be segmented into homogeneous regions. The homogeneity criterion may vary depending on the difference between the objects and their surroundings. Since shape, size and contrast are features of primary importance, the images need to be processed so that their structure is simplified but at the same time the relevant contour information is accurately preserved. Preservation of boundaries is a typical characteristic of connected operators, which differentiates them from other operators that perform their function locally thus affecting region boundaries. Some special cases of connected operators that were studied are the *reconstruction opening (closing)*, the *area opening (closing)*[8, 5], and the *levelings* [4]. These three operator types exploit the information concerning the contrast and size of soil grains and particles.

The greylevel reconstruction opening of an image f given a marker signal $m \leq f$ is:

$$\rho^{-}(m|f) = \lim_{n\to\infty} \delta_B^n(m|f), \quad \delta_B(m|f) = (m \oplus B) \wedge f \quad (1)$$

where δ_B^n denotes the n-fold composition of the conditional dilation δ_B with itself, and B is a unit disk. Reconstruction closing is defined dually by iterating conditional erosions:

$$\rho^{+}(m|f) = \lim_{n\to\infty} \varepsilon_B^n(m|f), \quad \varepsilon_B(m|f) = (m \ominus B) \vee f \quad (2)$$

The area opening (closing) of size n keeps only the connected components of the image foreground (background) whose area is $\geq n$.

The levelings are self-dual and hence treat symmetrically the image foreground and background; further, they include the reconstruction opening and closing as special cases. Compositions of reconstruction closings and openings are simple cases of levelings.

The *preprocessing stage* is of critical importance since its output detrmines the segmentation results. The soilsection image has to undergo a filtering in order to suppress the precense of noise and smooth the inside texture while preserving the boundaries of the grains. For this purpose, an ASF was used consisting of alternating openings and closings. The openings and closings were based on *reconstruction*. Given a feature/marker $m = f \ominus rB$, where $r = 1, 2, 3....$ within a reference image f, the reconstruction opening operator works by continuously growing the marker until all components of the reference f that are hit by the marker are completely reconstructed. As it was mentioned above, these filters by reconstruction belong to the class of connected operators that have the fundamental property of interacting with the image by means of flat zones [5]. They do not remove some frequency components (like linear filters do) or some shapes (like median filters or simple opening and closings do).What they actually do is removing and merging flat zones. Openings by reconstruction remove bright components that are smaller than the structuring elements which results to fill up the voids in soil grains or clusters and make them more flat and uniform. Similarly, since closings by reconstruction remove dark components that are smaller than the sructuring element, they eliminate very small soil grains and dark regions, and make the backround more uniform. Additionally, the combination of these reconstruction filters accomplishes image denoising without affecting the boundaries of the regions of interest. The result of the application of the ASF filter by reconstruction on the soilsection image that is shown in Fig.1 (a) is presented in Fig.1 (b). The soilsection image can be further simplified by using the area opening and closing operators. These operators are connected in the sense that they suppress arbitrarily shaped image components whose areas (number of pixels) are smaller than a given threshold. By applying these operators (an area opening followed by an area closing) to the soilsection image the obtained image consists of many flat regions. The threshold level determines the connected components that will be eliminated after filtering. Consequently, the value of the threshold can be chosen depending on the size of soil grains that need to be detected. An area closing with a relatively low threshold can suppress small dark regions, whereas an area opening with a ralatively high threshold can merge flat regions inside the boundaries of the soil grains, making the soil grains look darker and more uniform. The result is shown in Fig.1 (c).

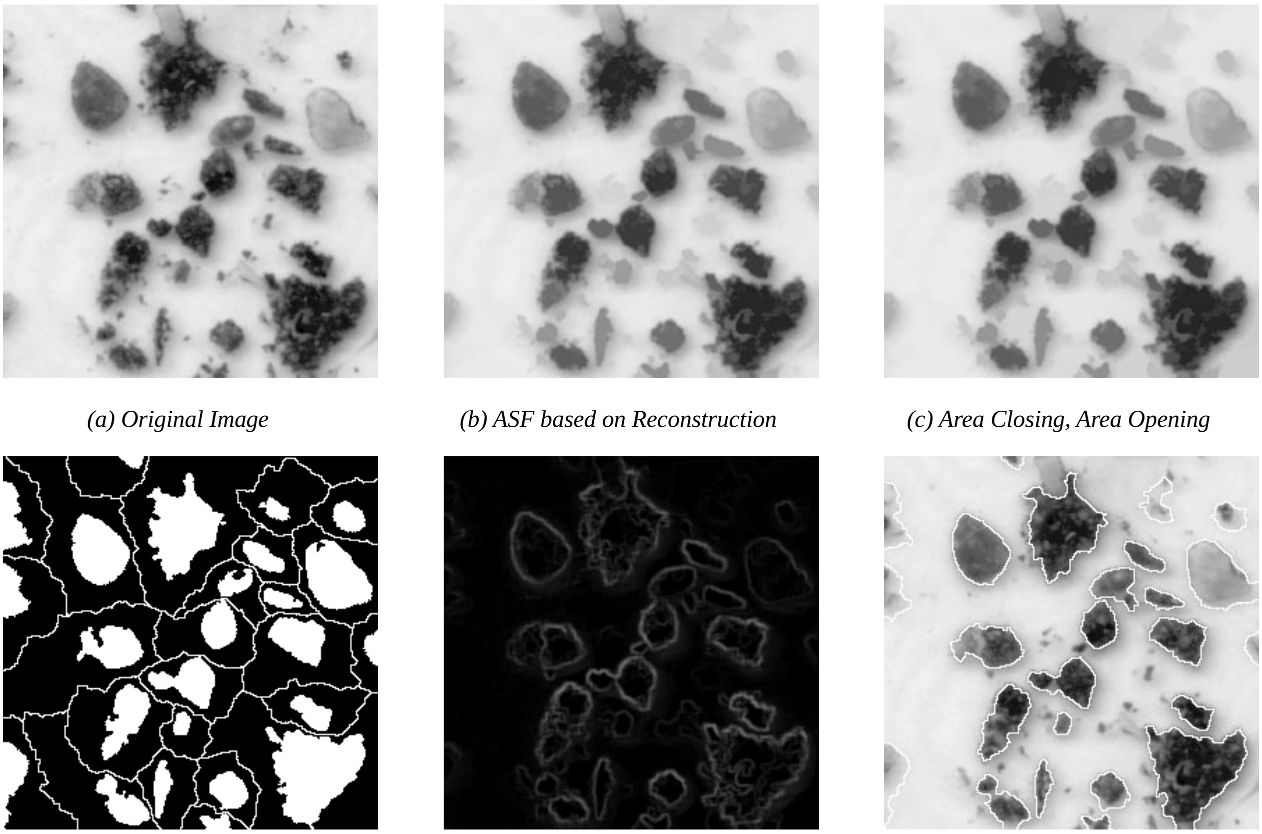
The *region-feature extraction stage* deals with the extraction of markers, which requires a more severe processing of the already filtered image [1]. In our work we extract constrast-related markers via the following procedure. First we perform a closing by reconstruction to the simplified image f that was obtained in the previous stage. The marker m used for the reconstruction procedure described by Eq.2 is the simplified image incremented by a constant h, $m = f + h$. The simplified image f is subtractred from the reconstructed image $\rho^{+}(f + h|f)$, and the resulting image residue is thresholded at level t. The obtained binary image is the set of markers that are included in the clusters of soil grains. These markers specify the location of the soil grains of a certain contrast that produce valleys of depth h. The threshold level t is analogous to the constant h. The size and shape of markers is not critical for the segmentation, but only their location and existence. This set of markers is called *Inside Markers* and corresponds to the soil grains. Another set of markers is needed to successfuly segment the image. This set is called *Outside Markers* and corresponds to background of the image. The marker for the background is extracted by flooding the filtered soilsection image using as sources the inside markers. The resulted watershed line is the outside connected marker (background marker). The final set of markers is the union of the two sets detected previously, $Markers = InsideMarkers \cup OutsideMarkers$, presented in Fig.1 (d).

The *watershed transform* is the final stage of the segmentation process. The morphological gradient (Fig.1 (e)) of the simplified image (Fig.1 (c)) is flooded. The sources are the inside and ouside marker detected previously. The watershed construction grows the set of markers until the exact contours of the objects are found. The contour of each soil grain (or cluster of grains) is necessarily between its inside and its outside marker. The watershed transformation is implemented via hierarchical queues [1]. The segmentation result of the soilsection image (after filtering) is presented in Fig.1 (f), superimposed on the original image. As it can be seen, most of the soil grains are detected. The ones that are missed, are of small size and low contrast compared to their local background. This was expected due to the filering that was performed on the image.

4. IMPROVEMENTS ON CONNECTED OPERATORS

4.1. The Concept of Connectivity Measure

In the previous sections, we referred to the application of connected operators, which are based on the underlying concept of connection (or connectivity) [7], such as the usual path-connectivity class $\mathcal{C}$ in an Euclideal topology. This concept, which is equivalent to the definition of a family of openings $\{\gamma_x\}$ called connectivity openings, can be extended using a variety of lattice operators. Let



(a) Original Image *(b) ASF based on Reconstruction* *(c) Area Closing, Area Opening*

(d) Set of Markers *(e) Morphological Gradient* *(f) Segmented Image*

Fig. 1. *Segmentation of Soilsection Image*

ψ be an increasing and extensive operator on the lattice $\mathcal{P}(E)$. Then it can be shown that a new connectivity class is obtained based on the following definition of connectivity openings:

$$\gamma_x^{\psi}(A) = \gamma_x\left(\psi(A)\right) \cap A, \quad \text{if } x \in A \tag{3}$$

(or else, $\gamma_x^{\psi}(A) = \emptyset$, when $x \notin A$). This is often called second-order (or clustering) connection. Based on this concept, the definition of a multiresolution connectivity measure was proposed in [2], quantifying the idea of a varying degree of connectivity. A special case of connectivity measure can be defined using morphological dilation operators, quantifying in fact the notion of "how close" are the disconnected components of a set as interpreted by the number of dilations needed for A to become connected.

However, what is needed in many image analysis problems is the inverse of the above, that is, to extract "strongly connected" (as opposed to "loosely connected") regions from an initially topologically connected set. The application of typical connected operators, such as the reconstruction openings/closings, leads to finding all connected regions of an image irrespective of the geometry of the path "tying together" these regions (that is, even if this path is "thin" and/or "long"). This form of connected morphological operator often presents the drawback of reconstructing "too much", which is called "leakage" problem resulting in the creation of undesirable connections between large objects in an image due to the existence of thin connected paths between them [6]. To cover such situations, the concept of connectivity is extended by introducing some new quantitative measures as described below. These generalized connectivity measures can be then used to develop a multiscale connectivity analysis framework based on the concept of "connectivity tree" for hierarchical image represntation.

4.2. Multiscale Morphological Connectivity Analysis

We propose the definition of generalized connectivity measures, as a means to differentiate between strong or loose connections within an image and establish a multiscale connectivity analysis framework. We illustrate this concept by an example. Let's consider the three different sets $A_1, A_2, A_3 \subseteq \mathbb{R}^2$, shown in Figure 2. Each one of these sets is initially topologically connected (A_1,A_2,$A_3 \in \mathcal{C}$). Intuitively, what we need to define is a connectivity measure $\mu(.)$, such that $\mu(A_1) > \mu(A_2) > \mu(A_3)$. In fact, $\mu(.)$ could be a non-negative function taking values $\mu(A) \rightarrow 0_+$ when A is considered "nearly disconnected", and $\mu(A) \rightarrow 1$ when A is "completely connected". We could thus define a *generalized connectivity measure* on the complete lattice $\mathcal{L} = \mathcal{P}(\mathbb{R}^n)$ as a non-negative function $\mu : \mathcal{L} \rightarrow [0, 1]$ satisfying the following condition:

$$\mu(\bigcup A_i) \geq \inf\left\{\mu(A_i), \mu(\bigcap A_i), \mu(A_i \setminus \bigcap A_i)\right\}, \; \forall A_i \in \mathcal{L}.$$

To differentiate between sets A_1 and A_2 of Figure 2 we could introduce a connectivity measure based on some anti-extensive morphological operator, such as erosion $\epsilon_B(.)$ (or opening $\gamma_B(.)$), indicating "how fast" a set $A \in \mathcal{C}$ becomes disconnected after the

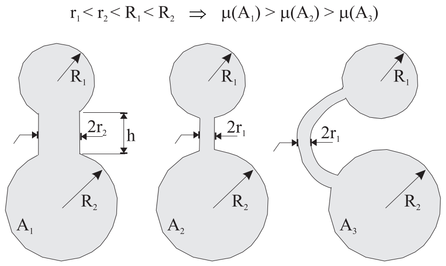


Fig. 2. *Generalized connectivity measure for three different sets*

recursive application of such an operator. In the rest of this paragraph, we use some form of exponential function to define connectivity measures. We can thus define an *erosion-based connectivity measure* $\mu_\epsilon : \mathcal{L} \rightarrow [0,1]$

$$\mu_\epsilon(X) = 1 - e^{-\lambda\, r_\epsilon(X)} \tag{4}$$

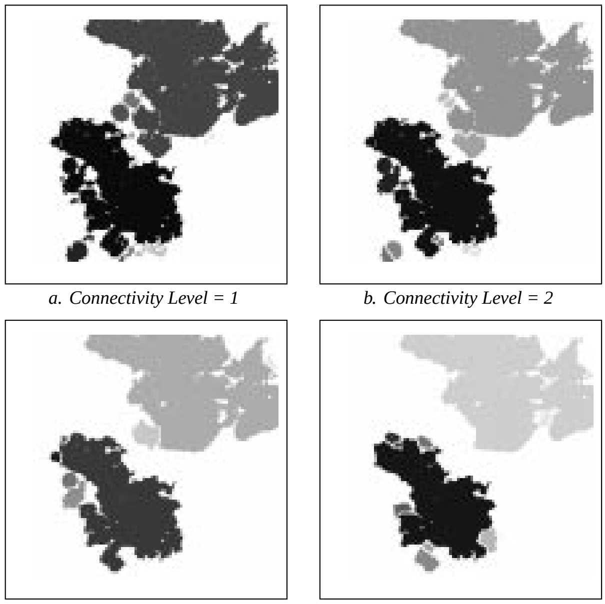
with $r_\epsilon(X) = \inf\{r \geq 0 :\ \epsilon_B^r(X) \notin \mathcal{C}\backslash\emptyset\}$ where $\lambda > 0$ is a parameter determining the rate of the exponential function. Applying this definition for the two sets A_1 and A_2 of Figure 2, we get: $\mu_\epsilon(A_i) = 1 - e^{-\lambda r_i}$ and $r_1 < r_2 \Rightarrow \mu_\epsilon(A_1) > \mu_\epsilon(A_2)$.

This erosion-based connectivity cannot distinguish though between the two sets A_2 and A_3. A different kind of measure must be defined to cover such situations, taking into account not only the "width" but also the "length" of the connecting paths. To extract such information, a dilation-based connectivity measure could be employed, such as the one introduced in [2]. However, this measure should be here extended based on the use of conditional (geodesic) operators, in order to take into account connectivity information (path geometry etc.) contained in the original set. Considering an adjunction $\alpha = (\epsilon_B, \delta_B)$ on the complete lattice $\mathcal{L} = \mathcal{P}(\mathbb{R}^n)$, we can then define a multiscale connectivity function:

$$\mu_\alpha(X, s) = e^{-\lambda\, r_\alpha(X,s)} \tag{5}$$

with $r_\alpha(X,s) = \inf\{r \geq 0 :\ \delta_B^r\,(\epsilon_B^s(X)\,|X) \in \mathcal{C}\backslash\emptyset\}$. This function incorporates, within a single *"connectivity profile"*, useful geometrical cues related to the "compactness" of a set in a continuous interval of scales, thus interpreting how "easily" this set becomes disconnected as well as the "distance" between its principal connected components (geometry of the paths connecting them together). Applying this definition for the example sets of Figure 2, we obtain for all scales $s > 0$: $\mu(A_1, s) \geq \mu(A_2, s) \geq \mu(A_3, s)$. We can then impose a connectivity profile $\bar{\mu}(s)$ as a thresholding function, partitioning an image into connected components X_i that satisfy: $\mu_\alpha(X_i, s) \geq \bar{\mu}(s),\ \ \forall s > 0$.

This concept can be used to establish the theoretical framework for a hierarchical connectivity image analysis. The basic idea lies in partitionning an image into progressively "stronger" connected components, leading to a hierarchical image representation that we call *connectivity tree* (or *C-Tree*). This representation incorporates geometrical information which can be particularly useful for the segmentation of soilsection images, where strongly connected soil formations need to be identified and differentiated from loosely connected regions (which in fact should be partitioned into a set of finer disjoint connected components). This concept is illustrated in Figure 3, which shows a typical "loosely connected" component (extracted from a sample soilsection image using classical connected operators) and its hierarchical recursive decomposition into four different connectivity levels, with increasing multiscale connectivity measure. This multiscale connectivity analysis can prove very useful for many image analysis tasks, including segmentation as well as granulometric image analysis and evaluation of soilsection images.



a. Connectivity Level = 1 *b. Connectivity Level = 2*

c. Connectivity Level = 3 *d. Connectivity Level = 4*

Fig. 3. *Multiscale connectivity partition of soilsection image*

5. CONCLUSION

This paper focused on the application of connected morphological operators to perform watershed segmentation of soilsection images. Reconstruction and area open/closings and levelings have been used and give satisfactory results despite the complex structure of the images. Furthermore, we introduced a threoretical framework for generalized multiscale connectivity analysis, which is used to develop improved connected operators.

6. REFERENCES

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