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Fast 3D Object Segmentation in X-ray Tomography

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Abstract: Segmenting objects or internal structures from volumetric images has found many applications in X-ray computer tomography. Owing to the data-intensive nature of these applications, increasing computational efficiency becomes a primary concern for the design and development of 3D object segmentation methods.

We propose an efficient deformable model with multiple templates to segment 3D vessel objects in X-ray tomographic images of wood. In our approach, an automatic vessel segmentation method is applied to the first image of the 3D sequence to obtain the initial template for object contours. A deformable energy minimization concept is applied, involving a balance between internal forces from spline contour stretching and bending and external forces from salient image features. The template then interacts with the adjacent frame and deforms iteratively toward the local target, which can be preserved as the input for the next frame in the sequence. This process is repeated for consecutive frames until the object leaves the field of view or a new object emerges. The deformable model is fast and accurate in tracking small object variation in a continuous space. However in our application, vessel diameters and orientations in most hardwoods can vary considerably along the longitudinal axis i.e. scanning direction. This may result in large variations in vessel shape and size from frame to frame, making it difficult to devise appropriate continuity constraints for contour shape. To prevent the propagation of deformable model errors, a new template is generated using the automatic object segmentation method to re-initialize the internal energy constraints of the deformable model. Multiple templates have proved to be particularly useful for processing large image volumes. Combining multiple templates with the deformable model provides an effective method for CT volumetric data segmentation and internal structure characterization.

The proposed method has been implemented in a dual-core system and used to segment vessels in X-ray tomographic images of eucalypt samples. A large series of images was acquired normal to the longitudinal axis of wood to obtain a set of transverse views of wood microstructure. Vessels in hardwoods form longitudinal tubes for water conduction and appear as approximately ellipsoidal objects in cross-sectional images. The automatic vessel segmentation method and the deformable model are applied alternatively for the entire image sequence to obtain 3D vessel contour information of the scanned samples. The automatic template segmentation is more computationally expensive than the deformable model; however only a few templates are required in our experiments (1 or 2 templates for processing 100 images). Vessels can be reconstructed in 3D from the segmented contour data and some important vessel properties, such as volume in wood, average length and diameter, can be measured accurately from the reconstruction.

Keywords: *Object segmentation, X-ray tomography, deformable model*

1. INTRODUCTION

X-ray computed tomography is a non-destructive imaging technique for capturing information relating to the interior structure of the examined objects. It was originally developed in medicine for visualization of soft-tissues and analysis of bone architecture and has now been extended to a wide variety of applications in materials, geological and biological sciences. X-ray tomography is used to generate a 3D reconstruction of the sample from a series of two dimensional views acquired at different angles of orientation.

We use an extension of typical tomography techniques in called x-ray phase-contrast microtomography to analyze the microstructure of wood and fibre composite materials with the aim of modeling their X-ray diffractometric behavior and thoroughly measuring wood properties. X-ray phase-contrast enhances the visibility of low-Z materials such as wood by exploiting refractive effects in addition to the x-ray absorption effects used in standard x-ray tomography. This enables the production of high resolution 3D reconstructions of wood samples suitable for image segmentation.

Segmenting objects or internal structures from volumetric images becomes an important and challenging task in many X-ray computed tomography applications. Most of these applications involve tracking object boundaries or shape variations in continuous temporal and/or spatial domains. Owing to the irregular nature of objects in most applications, deformable models have been widely used in modeling dynamic behavior of articulated object motion (Amini and Duncan, 1992, Park et al. 1996), and in segmenting geometric deformation of anatomical structures (Casseles et al. 1997, Holtzman-Gazit et al., 2006). Deformable contour models or well-known snakes (Kass et al., 1988), are based on the minimization of a cost function, often called deformable energy, that contains internal forces from spline contour stretching and bending as well as external forces from image features. Recent developments on deformable models have enhanced the framework by introducing application-oriented constraints in improving the deformable energy, such as gradient vector forces (Xu and Prince, 1998), topological controls and level set based approaches (Paragios, 2003, Zimmer and Olivo-Marin, 2005) for handling multiple objects. Each model has merits in some applications and limitations in others. The fundamental concept of deformable models, however, is generally applicable in solving many image segmentation problems.

The present work aims to segment vessels from X-ray wood images sequences in order to quantify vessel variations during tree growth. This task involves large quantities of data to be analyzed. Typically, one experiment generates several hundreds to thousands of images for analysis and many experiments need to be conducted to cover a wide range of wood species and diverse growth conditions. Computational efficiency becomes a primary concern in the designing and developing of 3D segmentation methods.

In this paper, we present a computationally efficient approach for segmenting and measuring vessel properties of hardwoods from X-ray tomographic image sequences. Our approach combines an energy-minimizing deformable contour model with multiple templates for fast tracking vessel variations along the longitudinal axis of wood. The method can handle multiple objects with no overlaps among vessel elements. Contour templates provide well-defined object initial descriptions that will speed up the convergence process during the deformable contour tracking.

Most of the deformable or active contour models use either relatively arbitrary or user provided initial contours to begin with, both of which have some drawbacks. A relative arbitrary initial contour increases not only the number of iterations in the contour updating process, but also increases the chances of negative interactions caused by imaging noise or sample defects. A pre-defined initial contour does give a good start but extra work is needed to manually mark contours, which is particularly impracticable for tracing multiple objects. We have developed an automatic vessel detection method for processing 2D microscopic images (Chen & Evans, 2004). The method will be used to define a master template that contains contour information for all objects at the first image. The deformation process on the next frame will be accelerated in terms of tracking small scale variations from the initial state.

The deformable contour algorithm is introduced in the next section with a specific description of vessel segmentation. Section 3 describes the X-ray imaging experimental design and shows some results on segmenting vessels for eucalypt samples. Section 4 discusses the performance of the model and concludes the paper.

2. DEFORMABLE MODLE FOR VESSEL SEGEMNTATION

2.1. Deformable contour algorithm

The deformable energy is defined as a continuity-controlled spline acted upon by an internal energy $E_{\text{int}\,ernal}$, an image energy E_{image} and en external energy $E_{external}$. A deformable or active contour is derived by minimizing the total energy functional to achieve an equilibrium position of the deformed contour. Suppose an active contour is parametrically represented by a vector:

V(s) = (x(s), y(s)) where 0 < s < 1

The total energy functional is formed by:

$$E(V(s)) = \int_0^1 E_{\text{int}\,ernal(v(s))}(V(s))ds + \int_0^1 E_{image}(V(s))ds + \int_0^1 E_{external}(V(s))ds \qquad (1)$$

The internal spline energy is a weighted combination of a stretching energy (first-order derivative) and a bending energy (second-order derivative) to control the continuity and the smoothness of the contour:

$$E_{\text{int}\,ernal}(V(s)) = \alpha \left\| \frac{dV(s)}{ds} \right\|^2 + \beta \left\| \frac{d^2V(s)}{ds^2} \right\|^2 \qquad (2)$$

where α and β are weights associated with continuity and curvature and can be adjusted to control the elasticity and stiffness of the contour.

The image energy is designed to attract the active contour to image features, such as primitive features of corners and edges or other high-level features of shape and object topology. The common image functional consists of image gradient force that moves the active contour towards the strongest edge of objects.

Difficulties may occur when object shape and size vary largely from frame to frame, making it difficult to maintain continuity constraints during the model iteration. In such a case, an external intervention is practically effective to locally guide the contour to the desired positions.

Minimizing the active contour model energy (1) is associated with Euler-Lagrange equation: $\frac{\delta E}{\delta V} = 0$, which can be discretized by finite differences to obtain an iterative solution [Cohen 1991]:

$$V^{k+1} = (A + h_t I)^{-1}[V^k + h_t g(V^k)], \qquad k = 0,1,2,... \qquad (3)$$

where V^{k+1} and V^k are the (k+1)-th and k-th iterations respectively. *I* denotes the identity matrix, h is a step constant. The coefficient matrix $(A + h_t I)$ is a penta-diagonal band symmetric matrix. Therefore, the iterative equation (3) can be solved using a common LU decomposition.

2.2. Vessel segmentation

Vessels are unique features presented in hardwoods. They form open-ended thin-walled longitudinal tubes for water conduction and appear as ellipsoidal objects in cross-sectional images. Figure 2(a) illustrates a transverse view of vessels in a micro-tomographic X-ray image of a eucalypt sample. Most hardwood studies rely on the accurate measurement of vessel properties, such as diameters, volume and dense distributions for the selected samples. In general, vessel size and distributions vary greatly with species and sampling locations. Figure 2 demonstrates an example of vessel diameters changing by 25% within a growth increment of 1 millimeter. It is obvious that 3D X-ray tomography technique is superior in terms of capturing internal change of vessels compared to any conventional 2D approach.

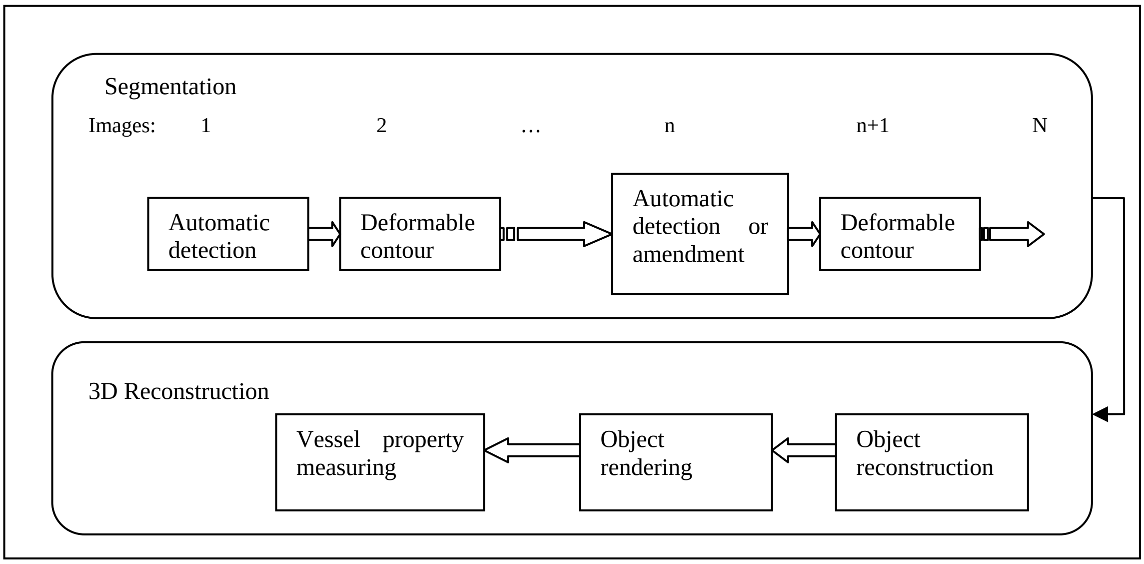
To measure vessel properties, we use the above defined deformable model (1) to tracking vessel contour variations through spatial domain. The model starts with an automatic detection of vessels at the first frame, which is applied as the master template for the deformable model. The automatic vessel detection approach combines object edge detection, shape analysis with a sophisticated object re-classification scheme to identify vessels from a set of abstract objects. The master template contains contour information for all vessels in the image and provides initial contour estimations for the adjacent frame. The automatically detected master template is often accurate if the sample does not contain internal defects such as cracks. Otherwise, the master template may need some local amendments to ensure a good initialization. The template then interacts with the immediate neighbor frame and deforms iteratively towards the local target, which can be preserved as the input for the next frame in the sequence. This process is repeated for consecutive frames until the object leaves the field of view or a new object emerges. In such a case, a new template is necessary for re-labeling vessel objects.

The deformable model is fast and accurate in tracking small object variation in a continuous space. However as we have discussed before, vessel diameters and orientations variations may result in considerable change in object shape and size from frame to frame, making it difficult to devise appropriate continuity constraints for vessel shape. To prevent the propagation of deformable model errors in our application, a new template is generated using the automatic object segmentation method to re-initialize the internal energy constraints of the deformable model. Multiple templates have proved to be particularly useful for processing large image volumes.

The automatic template detection is rather computationally intensive compared to the deformable model, as shown in Table 1. Therefore, we introduce a user-interactive force to locally guide a specific contour to the desired locations in order to minimize the number of the templates required in our model. It is very common in real image applications that random noise can be dominating over a small region so that contours in the affected area may be misled to wrong track. The user force is particularly convenient for local amendment without interfering with other objects.

2.3. Implementation details

The presented vessel segmentation model has been developed as an interactive graphical interface for processing volumetric X-ray images. The interface was implemented based on standard Windows graphical components and provides a set of user-friendly functions for controlling and monitoring the process. Figure 1 shows a conceptual diagram of data-flow for the proposed method.



The main feature of the software includes:

- Visualization – enable the processing results to be updated and displayed for visual inspection
- Batch processing – enables to process a collection of images at one command.
- User intervention – allows users to intervene the deformable process by adding a point force through the mouse event to correct local errors for a particular vessel without affecting rest of them.
- Controlled model parameters – allows users to tune the model parameters during the processing for dynamical control of energy weights in the deformable functional.

3. EXPERIMENTS AND RESULTS

3.1. Data Acquisition

Wood samples were cut into 1mm cubes from dehydrated increment cores that were taken from the breast height of living trees. The micro-tomographic image data of the wood samples were acquired using an X-ray ultramicroscope system (Mayo et al. 2003) to obtain a 3D reconstruction from which image sequences along radial, tangential and longitudinal directions could be extracted. The volumetric dataset contains 880 x 880 x 890 8-bit grey-scale voxels. Figure 2 shows two radial cross-sectional views of a eucalypt sample separated by 1mm (the first image and the last image of the longitudinal sequence). Vessels appear as ellipse-like objects with a thin-wall around each of them. Vessel diameter variations were observed by comparing the labelled measurements of a selected vessel from two images.

3.2. Results

The proposed method has been implemented in a dual-core system and used to segment vessels in the X-ray tomographic images of eucalypt samples. The automatic vessel segmentation method and the deformable model are applied alternatively for the entire image sequence to obtain 3D vessel contour information of the scanned samples. The automatic template segmentation is more computational expensive than the deformable model; however only a few templates are required in our experiments (1 or 2 templates for processing 100 images). Vessels can be reconstructed in 3D from the segmented contour data and some important vessel properties, such as volume in wood, average length and diameter, can be measured accurately from the reconstruction.

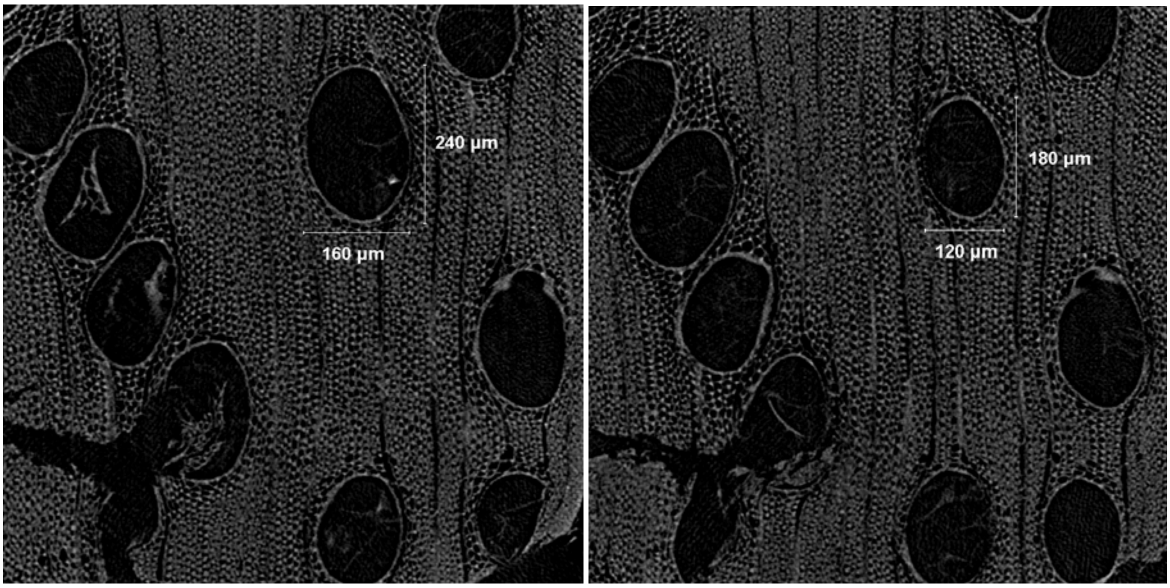


Figure 2: two transverse images of a eucalypt sample that are 1mm apart in the longitudinal direction. Diameters labeled for a selected vessel on the left image reduces by 25% on the right image.

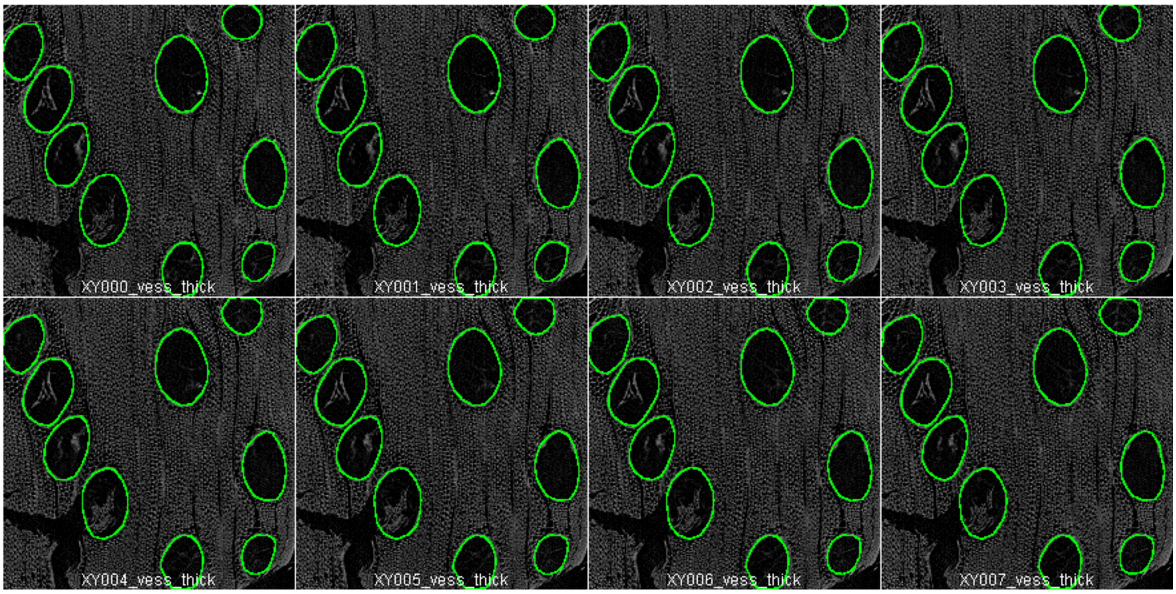


Figure 3: eight consecutive images with segmented vessels overlaid in green contours.

Figure 3 shows a montage view of 8 consecutive images processed by the proposed method. Segmented vessels are outlined in green for visual inspection. As we can see from these images, a crack in the bottom-left region has merged to a nearby vessel, which results in partial loss of the vessel wall as illustrated in Figure 4(a). The initial vessel wall is reconstructed for the missing area using an elliptical shape approximation (Figure 4(b)). Constrained by the shape continuity and contour smoothness, the following processing achieves an optimal approximation of the vessel volume in the damaged area.

The automatic vessel detection approach was originally developed for identifying vessels along transverse surfaces of radial strips, cut through the middle of wood disks. Our previous work (Chen & Evans, 2004) has examined the detection accuracy over a set of eucalypt samples and found that approximately 90% of vessels were detected by the automatic method. In the current work, the automatic method is applied only for small samples (less than 1mm in length) which have few vessels, however a similar detection accuracy is observed. For example in the testing sample shown in Figure 2, only one vessel in the bottom-left crack affected region was misdetected by the automatic method.

Table 1 compares computational performance of the deformable model and the automatic template detection method under different system configurations. It shows that the deformable contour model reduces the CPU time by 92% of the automatic detection method. Therefore, the automatic method is used only at the first image and occasionally at some stages where the number of objects is changed or most objects have an abrupt transition. For eliminating local errors, external intervention is more effective in terms of minimizing false interactions and preventing error propagations. Table 1 also shows that the accumulated computational power of the dual core system is significant for processing large image volume.

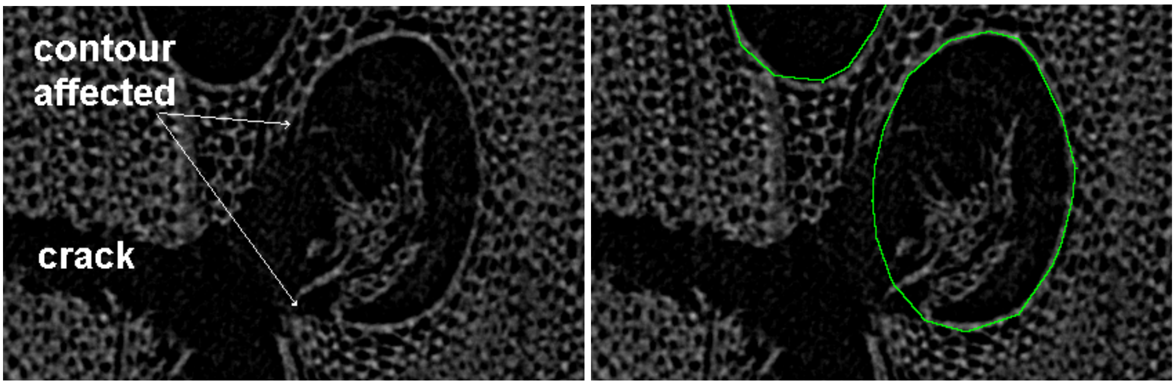


Figure 4: An enlarged view of a vessel at the left-bottom region where the vessel wall has broken by a crack (a); and a template wall contour reconstructed by elliptical shape constraint (b).

CPU seconds per image (880 x 880 pixels)	Automatic template	Deformable model
Single CPU	2.012 ± 0.041	0.155 ± 0.005
Dual core	1.325 ± 0.016	0.097 ± 0.007

Table 1 compares CPU performance of the automatic template detection method and the deformable model for processing an image of 880 x 880 pixels on both a single CPU machine and a dual-core system.

4. DISCUSSIONS AND CONCLUSIONS

We have developed a computationally effective method for 3D object segmentation from X-ray micro-tomographic images and demonstrated the use of the presented method in analyzing and measuring vessel properties for hardwood studies. The technique presented can be conceptually applied to analyze and characterize micro-structure and internal properties of other types of micro-porous materials. We will continue working on analyzing cell wall structures and measuring wall shape and orientation variations in order to gain a better understanding of X-ray diffraction behavior in wood fibre.

Combining multiple templates with the deformable model has proven to be an effective method for CT volumetric data segmentation and internal structure characterization. The computational efficiency improves greatly from the automatic defined object shapes and contour templates, which provide well-defined initializations and speed up the convergence of the deforming processing. The number of templates used in practical applications depends on the degree of object deformation. It has been shown (refer to Table 1) that the automatic template detection method is more expensive than the deformable model since it involves a few computing intensive tasks of object initial detection, re-classification, splitting and merging. Our experiments of segmenting vessels from eucalypt pulpwood used about 1 or 2 templates for processing 100 images. It was proven to be a good trade-off between providing accurate initializations and minimizing time costing functional calls.

We have also investigated the use of high-performance hardware, such as multi-core systems, to further improve the analysis and visual performance in 3D image processing. Our future work will focus on designing and developing computationally competitive methods for advanced graphical processing hardware.

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