

# Shape-Based Interactive Three-Dimensional Medical Image Segmentation

Kevin P. Hinshaw\* and James F. Brinkley†

\* Dept. of Computer Science and Engineering, Box 352350

† Dept. of Biological Structure, Box 357420

University of Washington, Seattle, WA 98195

## ABSTRACT

Accurate image segmentation continues to be one of the biggest challenges in medical image analysis. Simple, low-level vision techniques have had limited success in this domain because of the visual complexity of medical images. This paper presents a 3-D shape model that uses prior knowledge of an object's structure to guide the search for its boundaries. The shape model has been incorporated into SCANNER, an interactive software package for image segmentation. We describe a graphical user interface that was developed for finding the surface of the brain and explain how the 3-D model assists with the segmentation process. Preliminary experiments show that with this shape-based approach, a low-resolution boundary for a surface can be found with two-thirds less work for the user than with a comparable manual method.

**Keywords:** interactive 3-D image segmentation, constraint-based shape models, knowledge-based medical imaging

## 1. INTRODUCTION

One of the key problems in medical image analysis is accurate image segmentation. In applications such as brain mapping and radiation treatment planning, 3-D reconstructions of biological structures are generated from computed tomography (CT) or magnetic resonance (MR) images of patients. Before the objects can be reconstructed their boundaries must be identified. Automatic methods for finding these boundaries often fail because of low contrast between adjacent soft tissues; frequently segmentation must be done manually to get acceptable results. Yet the goal is to locate a small number of objects, each of which has certain shape characteristics that hold across a wide spectrum of patients. Shape knowledge about these objects could be applied during the segmentation process to guide the search for clear edges and infer boundaries in regions of low contrast.

Shape models have been employed successfully in machine vision for years,<sup>1</sup> but the methods used generally work only with rigid objects. Consequently they have had limited applications in the medical imaging domain, where flexible structures are the norm. *Deformable models* (also known as snake or balloon models) offer a different approach that has gained considerable popularity. First introduced by Kass *et al.*,<sup>2</sup> the idea behind deformable models is to treat segmentation as an optimization problem, typically by minimizing an energy function that rewards boundaries that are locally smooth and pass through high-gradient image regions. However, deformable models usually lack *a priori* information about the shapes they are seeking, so they can easily be pulled toward erroneous intensity changes that do not correspond to actual object boundaries. The initial model must also be close to the correct surface.

An alternative to deformable models is a *geometric constraint network*, which we have proposed as a flexible, generic model for representing the shape and range of variation of biological structures.<sup>3</sup> The hypothesis behind this representation is that networks of local constraints, interacting with each other, are enough to define the shape and range of variation for a class of similar shapes. A specialized, 2-D version of a geometric constraint network, called a *radial contour model*, stores constraints describing the relative positions of discrete points around the boundary of a region, and has been shown to be useful for guiding 2-D image segmentation.<sup>4</sup>

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Other author information: (Send correspondence to KPH)

KPH: Email: hinshaw@cs.washington.edu; WWW: <http://www.cs.washington.edu/homes/hinshaw/>

JFB: Email: brinkley@u.washington.edu; WWW: <http://www1.biostr.washington.edu/>

In this paper we extend the radial contour model to 3-D, so that a single shape model can describe a complete surface. Section 2 presents a method for representing surfaces and explains the process of building shape models from training data. The section also describes SCANNER, an interactive system for constructing shape models and surfaces. Section 3 provides experimental segmentation results, and section 4 discusses the findings and future directions for this project.

## 2. METHODS

### 2.1. Surface representation

We represent a surface as a series of parallel slices, as illustrated in figure 1. The center points for the slices are collinear, forming an axis that runs perpendicular to all the slices. At given intervals along the axis, radials are extended outward in the slice plane to the surface boundary. Each surface also has a local coordinate system that describes its orientation within a 3-D space. The coordinate system is derived from landmarks that provide translation, scale, and rotation information. We have chosen to use evenly spaced slices, each of which has a fixed angle between its radials. It is also assumed that each radial will intersect the surface only once. (In 2-D, a contour satisfying this condition is sometimes called *star-shaped*.) Despite this limit on the class of describable shapes, this representation is flexible enough to be used for shape comparison and for guidance of low-level segmentation methods.

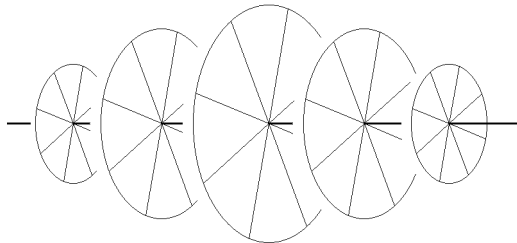
### 2.2. Capturing shape with the radial surface model

Given a set of radial surfaces as training data, shape information can be extracted and used to build a model describing the set. Ratios of radial lengths are used as local shape features; for a pair of radials  $i$  and  $j$  with lengths  $r_i$  and  $r_j$ , the ratio is simply  $s_{ij} = r_i/r_j$ . Radials for which a length ratio is computed are referred to as *neighbors*.

How many of these features should be measured? In 2-D, a contour has a small number of radials, so it is reasonable to treat all radials as neighbors and compute ratios for every pair. In 3-D there are considerably more radials, making this strategy less attractive. Therefore, length ratios in the 3-D model are computed only between a radial and its four most immediate neighbors: the two radials beside it in its slice, plus the radials directly above and below it on adjacent slices.

Once shape features have been measured for each surface, they can be used to derive constraints for a *radial surface model*. For each pair of radial neighbors  $i$  and  $j$ , the model stores a lower bound,  $L_{ij}$ , and an upper bound,  $U_{ij}$ , which correspond to the minimum and maximum values that were seen in the training set for ratio  $s_{ij}$ . These bounds are the model’s shape constraints. By itself, a radial shape model gives no specific information about a surface’s location. The model stores local shape *relationships*, which are meaningless without some point of reference. But as soon as a single radial has been specified, the constraint network can be used to derive possible surface locations.

The user instantiates a shape model for a given volume dataset by indicating a set of landmarks in the volume data. These landmarks define the model’s local coordinate system within the image volume, and may also provide initial values for one or two radials. A constraint propagation algorithm is invoked to find the values for the remaining radials that are consistent with these starting points. Suppose that radial  $j$  is initialized to have length  $r_j$ . For each of its neighbors  $i$ , the constraint  $L_{ij} \leq s_{ij} \leq U_{ij}$  can be used to infer that  $L_{ij}r_j \leq r_i \leq U_{ij}r_j$ . The neighbors of  $j$  are now bounded, because the constraints have been used to rule out values that were not observed in the model’s



**Figure 1.** The radial surface representation. A series of parallel slices, with evenly-spaced radials extending out from the center of each slice to the surface boundary.

training set. The updated neighbors can in turn be used to bound *their* neighbors, creating a wave of updates that propagates through the whole surface. During segmentation, an *uncertainty interval* is maintained for each radial to keep track of which values still satisfy the constraints. Details about the propagation of shape constraints were presented earlier for the 2-D case.<sup>4,5</sup>

### 2.3. Shape models in action

An example should help to clarify how these shape models are used to aid segmentation. The images in figure 2 illustrate how this process works with a shape model of the cerebral cortex that was derived from three hand-drawn surfaces. The first two images each show two surfaces — the darker, inner one connects the radial lower bounds; the lighter, outer one connects the upper bounds. The space between them is the uncertainty region where the actual surface is expected to fall.

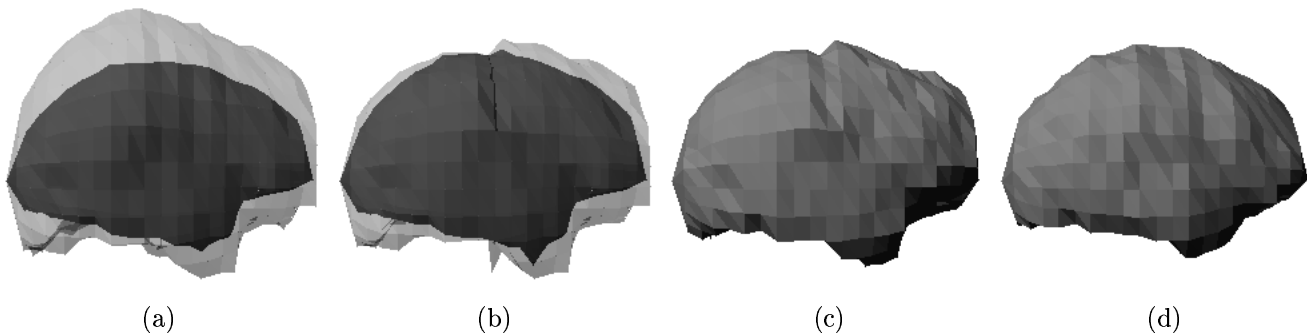
Given a cortex shape model and a volume dataset to segment, the user specifies landmarks to orient the model in the dataset, plus a single radial length on the middle slice for initialization. (Details about these landmarks appear in section 2.4.) Figure 2a shows the uncertainty region for the surface after the radial has been propagated. Note that the bounding surfaces shown were generated solely by the propagation of the single radial through the model's constraint network, yet the surface already looks brain-like.

At this point, an automated search-and-propagate phase begins. The uncertainty intervals for the remaining radials on the middle slice are searched with a one-dimensional edge detector. Where edges are found, exact radial lengths are computed and the uncertainty is reduced to zero. After the entire slice has been searched, these new radial lengths are propagated through the constraint network, resulting in the surface shown in figure 2b. The bounds are much closer together than before because the extra radials and their relations to neighboring radials have been used to tighten the uncertainty intervals. The edge detector is then applied to the slices adjacent to the middle one. The cycle of searching a slice and propagating new edges moves from the center slice outward, until all of the radials in the surface have been searched. For any radial with remaining uncertainty, a location is guessed by taking the midpoint of its uncertainty interval. (Figure 2c.) At this point, the user can manually correct any errors made during the search-and-propagate phase. (Figure 2d.)

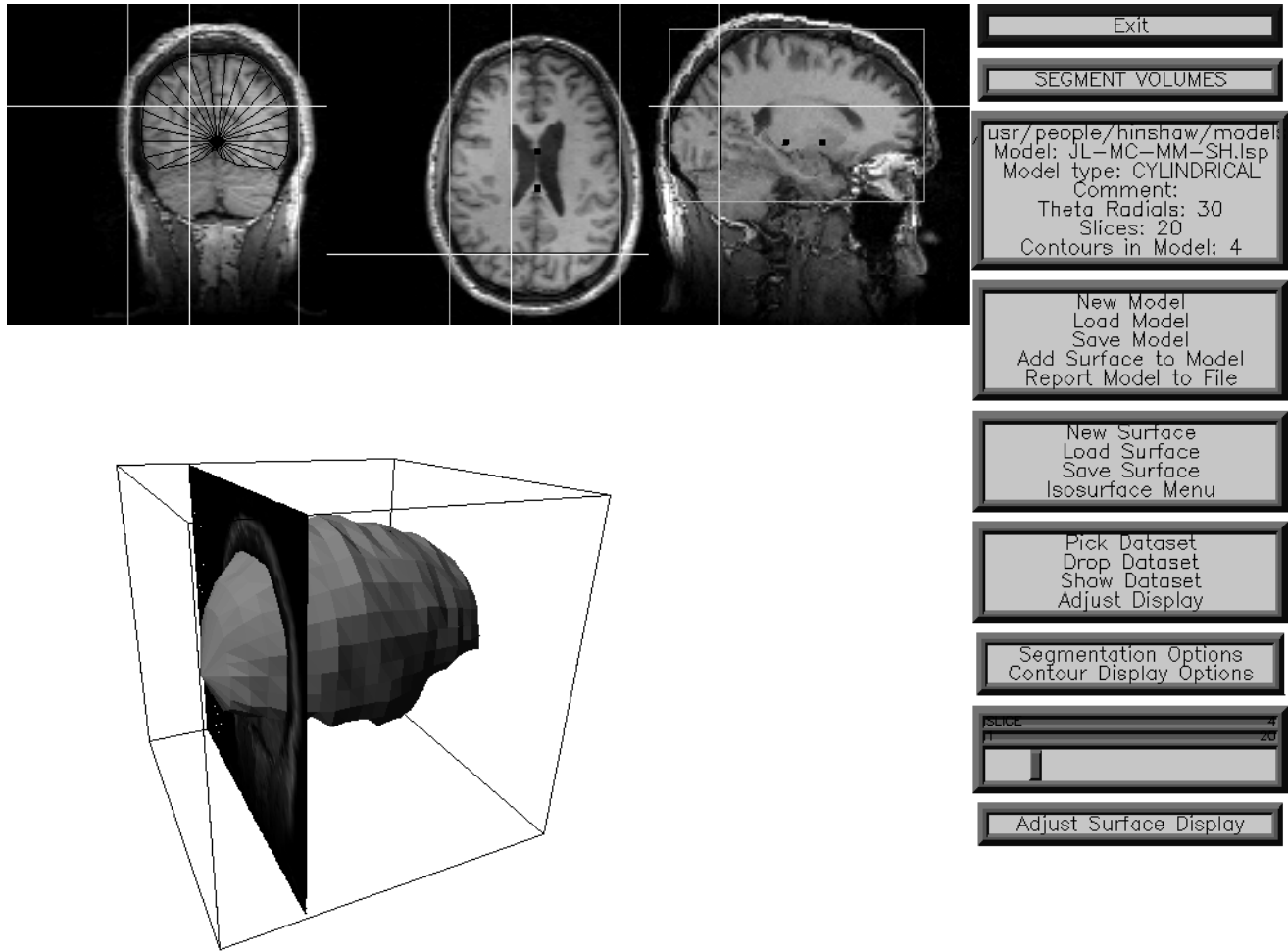
### 2.4. Scanner

The radial surface model has been incorporated into SCANNER, an interactive image segmentation system. SCANNER runs on Silicon Graphics machines and is built using a hybrid Lisp-C language called Slisp.<sup>6</sup> Figure 3 shows the interface for SCANNER.

We have designed a 3-D surface editor for building radial surfaces. This editor is useful both for drawing training surface data by hand and for correcting mistakes made during the automatic segmentation stages. The interface



**Figure 2.** Progression of propagated shape constraints for a radial surface brain model. (a) The inner (dark) and outer (light) uncertainty bounds after a single radial has been entered and propagated. (b) The intervals after an edge detector has searched the central slice and the results have been propagated. (c) The final surface found by the search-and-propagate phase. (d) The surface after it has been corrected by the user.



**Figure 3.** Scanner’s interface for brain segmentation. Three orthogonal slices through the volume data appear at the top. Crosshairs on the images mark the locations of the other two slices, and other overlays show the landmarks for the Talairach coordinate system. The surface view in the lower left displays the segmented surface within the volumetric data’s bounding box. The surface slice currently being edited is overlaid on the coronal plane at the top left, and the corresponding image slice is displayed in the surface view for reference. The system’s menu appears at the right.

shows three orthogonal slices through a volume dataset: a coronal view on the left, an axial view in the middle, and a sagittal view on the right. On each view, draggable crosshairs control the position of the other two slices. When a surface is being edited, the current slice is superimposed on its corresponding image. The editor also shows a 3-D view of the surface, along with a box representing the bounds of the volume dataset and the image slice currently being edited. Camera controls allow users to adjust the view of the surface, so that they can better visualize its spatial features.

The design of the interface was greatly influenced by the current limitations of 3-D interface technology. The goal was a system which would allow users to construct 3-D surfaces. While 3-D sculpting tools exist, the only techniques we found that addressed the issue of sculpting a surface embedded in a volume dataset were contour-based. Therefore SCANNER provides the user with traditional 2-D tools to edit individual slices of a 3-D surface. When better paradigms for 3-D surface editing are developed, the flexibility of SCANNER should make it easy to incorporate them.

For brain segmentation, a graphical user interface was designed to use the Talairach coordinate system,<sup>7</sup> which is commonly used in studies of the brain. The user follows these steps to define the Talairach coordinate system for a volume dataset:

1. Select the slice closest to the mid-sagittal plane.
2. On that slice, mark the superior border of the anterior commissure and the inferior border of the posterior commissure. (These points define the *AC-PC line*.)
3. Position a bounding box around the the cortex which just includes the top of the parietal lobe, the bottom of the temporal lobes, the back of the occipital lobe, the front of the frontal lobe, and the sides of the parietotemporal lobes.

The assumption is made that the mid-sagittal plane is nearly perpendicular to one of the axes of the volume dataset; in other words, the patient's head was not tilted to the side significantly during the imaging process. After the mid-sagittal slice and AC-PC line have been defined, the remaining axes for the surface coordinate system are inferred. (One of these runs perpendicular to the AC-PC line in the mid-sagittal plane, and the other is perpendicular to the first two.) Talairach-aligned bounding box lines are then superimposed on the three orthogonal slices for the user to adjust. A rectangle on the sagittal slice is used to control bounds for the top, bottom, back and front, while vertical lines on the other two slices control lateral bounds. (See figure 3.)

When all of the Talairach landmarks have been positioned, the volume dataset is rotated to align its axes with the surface coordinate system. There were two reasons for performing this realignment. First, this rotation makes the three orthogonal slices correspond more closely to those appearing in the Talairach atlas. This should make it easier for users to identify structures when tracing them by hand and using the images in the atlas as a reference. Second, surface editing should be made as easy as possible. The most straightforward approach is to use simple 2-D contour editing, but the surface slices are tilted relative to the MR data slices. Rotated images could have been generated for just the positions where surface slices fall, but for manual segmentation it is often useful to be able to scan quickly through the images in the neighborhood of the current one. It made more sense to realign the whole dataset at once than to compute rotated images on-the-fly.

Following this rotation, a radial surface is created by the propagation techniques described in the last section. Slices are positioned in the newly rotated coronal plane, with their centers coinciding with the AC-PC line. The front-to-back dimension of the cortical bounding box is used to determine the spacing between slices.

### 3. EVALUATION

SCANNER's performance was tested on MR volume data from four different individuals. First, the cortical surface for each dataset was segmented by hand, using SCANNER's surface editor to draw surfaces with 20 slices and 30 radials per slice. These surfaces were used for a series of leave-one-out experiments. Four brain models were constructed, with each one using a different set of three hand-drawn surfaces as training data. Each model was then used to segment the fourth volume dataset, and the result was compared to the manually drawn version. To simulate user initialization of the segmentation process, the Talairach coordinate system landmarks for each dataset were taken from the proper hand-drawn surface.

SCANNER is an interactive system, but it should still do as much automatic segmentation as possible. Thus the best segmentations are those that achieve accuracy with the least amount of intervention from the user. Therefore an extracted surface's quality can be gauged by counting the total number of radials that the user specified to define it. This measure has two components: the number of radials given as initialization, plus any corrections that must be made to bring the surface into agreement with the MR images. It was assumed that a user would correct any radial in the segmented surface which differed from the hand-drawn surface by more than 4 pixels.

Experiments were run using the search-and-propagate strategy described in section 2.3. The model was initialized with a single radial from the hand-drawn surface, constraints were propagated to shrink the uncertainty bounds, then alternating phases of edge detection and constraint propagation were run until all radials had been searched. Of the 600 radials in the segmented surface, the simulations showed that an average of 398.5 were within the 4-pixel

error tolerance of the corresponding hand-drawn radial. Since defining this surface manually would require drawing all 600 radials, the shape model reduced the amount of work required from the user by nearly two-thirds. Other search strategies were investigated, and they gave comparable results.

#### 4. DISCUSSION AND FUTURE WORK

The results in the previous section show that (1) the 3-D radial surface model captures the essential shape and range of variation of objects solely by the interaction of local shape constraints, and (2) the model, when implemented in a 3-D user interface, is useful for semi-automatic segmentation from volume datasets.

The usefulness for segmentation can be improved by developing alternate representations and search strategies. For example, other neighborhood patterns might provide tighter bounds, and it may be better to use a more hierarchical approach to constraint propagation. Rather than always propagating new information throughout the entire constraint network, propagation could be limited to smaller sub-networks most of the time, with periodic communication between the sub-networks. Methods for retracting information, perhaps using backtracking or optimization, would also reduce the influence of edges that are incorrectly chosen.

The segmentation computed with the aid of a radial model will be useful in itself for applications where highly detailed surfaces are not needed. Possibilities include finding organ boundaries for radiation treatment planning and measuring cardiac wall motion and volume. The model could also be used as a starting point for other segmentation methods. For example, one of the major drawbacks of deformable models is that they must be initialized with a boundary that is close to the correct one. A 3-D shape model could be used to find that starting point. The shape constraints could also potentially be incorporated directly into the cost function of a deformable model. This combination would be similar to the active shape model of Cootes *et al.*,<sup>8</sup> which incorporates statistics about the relative locations of boundary points for a set of training contours. The model's shape information is used to constrain a curve so that it can deform only in ways that were observed in the training set.

Another possibility would be to combine a radial surface model with an isosurface extraction algorithm. After locating a low-resolution surface with our semi-automatic method, the vertices could be treated as seed points on a single isosurface. The uncertainty bounds from the shape model could be used to supply a focused region of interest, preventing unwanted leakage into nearby structures with similar intensity values.

At the heart of both the 2-D and 3-D radial models is the hypothesis that networks of interacting constraints can represent both the shape and range of variation of biological structures. The current 3-D results further confirm this hypothesis, and suggest that more complex constraint networks will capture additional biological shapes, eventually leading to constraint-based representation of spatial anatomic knowledge.

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