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A System for 3D Surface Models from 2D Sectional Imagery

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ABSTRACT

Polygonal models in 3D, generated from 2D sectional imagery, are more flexible than volume visualizations, since as vector objects they can be flexibly scaled and manipulated. We discuss a semi-automated system which we have been evolving, in which a trained anatomist traces the detailed outline of a structure on a series of images, and from that series of contours a 3D polygonal model is created. To make best use of the expert, the system can learn the characteristics of their tracing from exemplars, and automatically trace ahead to ease and speed their task.

KEYWORDS: 3D models; visualization; machine learning; image processing

1. BACKGROUND

There are two distinctly different approaches to creating 3D models from 2D sectional imagery: volume visualizations vs. polygonal modeling. In a volume visualization, the sequence of 2D images are stacked on top of one another and a 3D matrix of voxels is created. Standard 2D image processing functions, generalized to 3D, can then be used to isolate and display structures in the volume. For example, bone is easily isolated in CT imagery by thresholding the image between certain values – the resulting structure can then be rotated in space for different perspective views. In the polygonal modeling approach, as seen in Figure 1, outlines of a structure of interest are defined on each image plane, and then these outlines are stacked (rather than the images) and triangles drawn between the outlines to create a polygonal mesh. Standard techniques from computer graphics can then be used to render the mesh, giving it a solid surface appearance, with various lighting conditions specified.

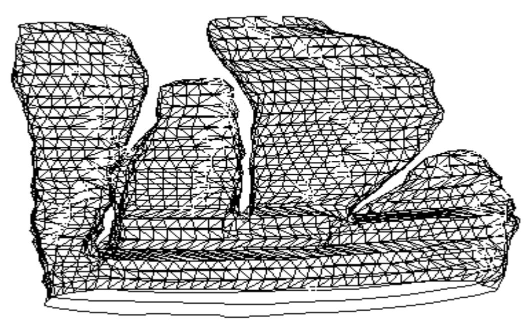

Figure 1: a triangulated mesh

Tools can generate volume visualizations reasonably quickly, once the voxels of interest have somehow been specified. However, it is difficult to separate structures in areas of low contrast, or in areas where the boundaries between structures are indistinct (for example, in separating one specific muscle from a larger muscle mass). Polygonal models, also called surface models, will be more difficult to construct initially, since the structure must be identified and outlined on each of the 2D images. However they bring with them significant advantages:

- They are usually a more compact representation of the structure.
- The surface can be easily manipulated (smoothly resized, deformed, etc.).
- They can be directly imported into CAD programs, for example, when designing biomedical instrumentation.
- They can be realistically presented through texture mapping (for a model of a human lung, we photographed a live lung during surgery and used that texture on the surface model).

Potential uses for such models are broad, encompassing researchers, educational experts, diagnostic needs, multimedia publishing, interactive simulation design, surgical device manufacturers, and entertainment specialists [McCracken & Spurgeon, 1991]. The construction of high-fidelity polygonal models are an essential feature of all of these applications.

The creation of these surface models involves three steps: tracing contours on the individual images, triangulating across the stack of contours, and then rendering the final model. The system we present here has evolved over ten years, and is now in its third generation. This most recent round of development effort was funded through an SBIR program grant through NSF.

2. THE SYSTEM

2.2 Tracing

To develop highly accurate models, we have anatomists trace structures of interest on the many sectional images in which it appears. While time consuming, they are able to make the judgment calls necessary to accurately define a structure when the imagery is confounded by inadequate structural definition in the pixels. We have used machine learning techniques to aid the anatomist in this tracing task.

While classical edge-detection methods do exist; for the medical images we are using, they have proven either insufficient, or they require more manual intervention than it would take to simply trace the contour manually. User-guided methods, such as Snakes [Kass, et.al, ‘87] and Live Wire [Mortensen & Barrett, ‘98] techniques, bth have problems in areas of high curvature, though this is overcome by various degrees of user intervention. More problematic, though, is the reliance of them all on a priori assumptions about what exactly constitutes an edge, for example the assumption that the greatest change in pixel intensity in an image corresponds to a specific edge of interest in the real world. In high-contrast, high-resolution, noise-free imagery, the classical & standard edge-detection techniques can work quite well. But in a less-then-ideal world, with imperfect sensors and random anisotropic noise, a priori assumptions will often break down.

Our approach is to use neural networks to assist an expert in the region delineation task. As a person begins tracing an anatomical structure, this data is used to train a neural network to follow the same contour in the image which the expert is tracking visually [Crawford-Hines & Anderson, 1997].

Figure 2 illustrates a case in point. This image is a detail from a CT through two legs, where the image parameters are tuned to highlight muscle tissue. We thus know that we should be seeing a mass of muscle with a layer of skin around it. The strongest boundary in the image is the exterior of the skin, but in this case the boundary of interest is several pixels inside that, the boundary between skin & muscle. Looking at the Raw Image, observe that in the upper leg, a weak boundary is reasonably well defined, a few pixels to the inside of the stronger external skin boundary. However in the area highlighted, this weak distinction becomes lost. When manually tracing the muscle/skin boundary, though, a human can adjust for the noisy image and continue to trace a few pixels to the inside of the skin. In this case the true boundary is confounded in the image by both noise and a much stronger boundary close by.

The lower half of Figure 2 illustrates the benefits of a learned boundary definition for these muscles. The upper boundary was manually traced by an anatomist. Based on those characteristics, a boundary definition was learned and then the lower boundary was automatically traced based on that definition. Notice the learned boundary tracks cleanly through the problematic area discussed above.

The neural network used to learn the boundary is a basic backpropagation network with one hidden layer. The output layer is trained to estimate the probability of the next point (as the contour is incrementally traced) being on the contour or not. At it simplest, normalized RGB or greyscale values in the local neighborhood can be used as inputs; preprocessing the image data (for example generating Gaussians at several scales) and feeding that to the network as inputs improves learning speed and trace quality. The tradeoffs among various input representations and analysis of the representations learned by the hidden layers are still under study.

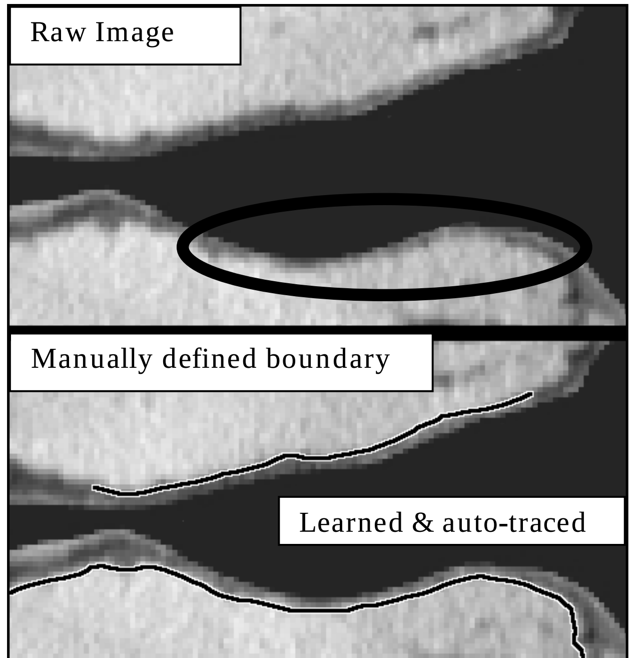

Figure 2: Leaning a Boundary

Triangulating

After contours are created for the structure in question on each of the relevant 2D slices, these contours must be triangulated to produce a final polygonal model. Triangulation between parallel contours is relatively straightforward if the contours do not bifurcate; however in anatomical structures this happens frequently, a prime example being the palm of the hand splitting into the five fingers. Although the triangulation problem becomes more complicated in this case, we have developed techniques to handle such cases which produces excellent models [Alciatore & Miranda, 1992; Fedde, 1993; Miranda, et al., 1990]. The input to this procedure is to decide which contours on one level need to be connected to which contours on adjacent levels. This "connectivity" question is crucial in producing accurate models.

The most complicated case we have seen so far in our work on the Visible

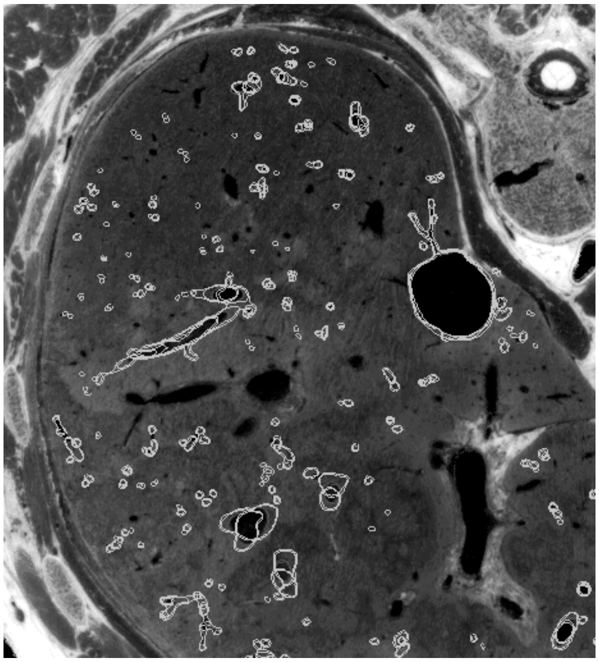

Figure 3: Liver cross-section, with hepatic veins traced

Human data is that of the hepatic vein (see Figures 3) for which relatively subtle decisions must be made on nearly every level as to which contour is connected to which.

The tracing and triangulating can work together as shown here in Figure 4.

Manipulating & Rendering

The models are saved in the OBJ format, a de-facto standard among 3D modeling programs. Thus the rendering is independent of our system once the polygonal mesh is created. Over the years, we have used Alias/Wavefront, Electric Image, and StudioMax to animate and render the surface models we've created.

A stand-alone tool, Sculpt, was developed for manipulating the polygonal mesh [Alciatore & Wohlers, 1996]. In addition to repairing holes in the mesh, the model can be deformed in several ways. Sculpt is a general-purpose mesh manipulation tool; it reads and writes several formats used by the major CAD programs in the market today.

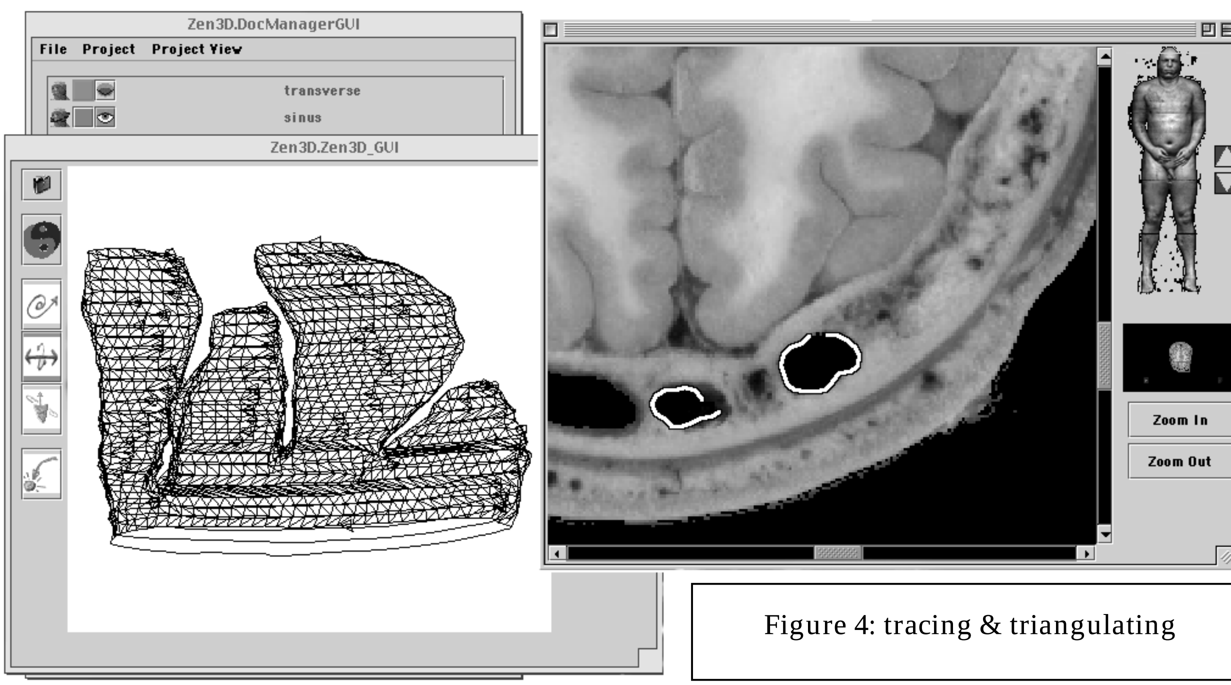

Figure 4: tracing & triangulating

SOME RESULTS

In Summer 2000, tracers at Visible Productions retraced the skin of the Visible Human, using an initial implementation of this automated tracing methodology in their production tracing system. The skin, largest organ in the body, and is represented on all 1,800 images in the Visible Human cryosection set. The skin boundary is fairly uniform, and incredibly tedious to manually trace in its entirety. One reason for the re-tracing is because of inconsistencies in the original boundary tracing. While there are no experimentally accurate records of how much time was taken to trace the skin boundary initially, those who did the first skin tracing estimate it took on the order of 3-4 weeks. With the automated assist, the skin was retraced in 3 days. Additionally, these new skin boundary contours are what is used in Visible Productions current models, since they are more globally consistent than the prior set of skin boundaries.

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