Automatic 3D segmentation of high resolution breast tumors in mice using region growing, active contours and gradient vector flow

N. Rajguru[1], J. Rodriguez[1], M. Runquist[1], J. Neville[1], C. Howison[1], R. Gillies[1]

[1]University of Arizona, Tucson, AZ, United States

Abstract A method to segment heterogeneous tumor lesions from high-resolution T1-weighted spin echo images is presented. The proposed algorithm combines 3D region growing with a level set approach. The ellipsoid, modeled on the output of the region growing process, is used as the zero level set for the narrow band level set segmentation. The level set function is sensitized to the actual boundary of the lesion by combining forces derived from the image near the lesion boundary, including gradient vector flow. Since there are no standard markers (as in brain) that can be used, the local probability near the lesion boundary is harnessed. The segmentation is achieved using fewer iterations than the classical level set method with narrow band approach, and is more accurate than using just the 3D region growing scheme.

Introduction In our study of high-resolution MR images of subcutaneous MDAmb231 tumors in laboratory mice, the goal was to segment the lesion volumes from the rest of the mouse body in contrast-enhanced T1 weighted MR data acquired at different resolutions. We accomplished this using a combination of 3D region growing and a 4D implicit function, known as the "level set"[1]. Segmentation of a region of interest (ROI) from a medical image is not always straightforward because of several problems such as noise, intensity inhomogeneity and boundary complexity (topology), spatial skewness, and inconsistent contrast. The problems are more pronounced and the solutions more computationally expensive when applied in 3D. Problems that needed to be addressed during segmentation of lesion volumes in these data sets were intensity heterogeneity of the ROIs (tumors) and poor contrast. Multi-slice 2D segmentation schemes, using region growing with centroid propagation [2] from slice-to-slice, failed because of the intensity inhomogeneity of the lesion volume. Also, using 2D schemes make the segmentation process time consuming and error prone for heterogeneous ROIs such as those under study. Hence, we used a 3D segmentation scheme - combining 3D region growing and a level set active surface approach to address the problem. The speed function of the level set was enhanced using gradient vector flow [3], and the decision to grow or shrink at the lesion boundary was made using local probability criteria. Previous methods [4] used the EM criteria to determine the probability, but since there were no permanent markers (such as in the brain) that can be used to model the segmentation process, the intensity information near the edge was used. The resulting level set had increased sensitivity to the edge (because of close initialization to the edge and the GVF forces). The proposed segmentation process produced similar results to using level sets alone, but in fewer iterations. Also, the results were more accurate than using just 3D region growing.

Methods The study consisted of magnetic resonance images of MDAmb231 tumors grown in the mammary fat pads of SCID mice, imaged 2-3 weeks after inoculation. The T1-weighted 3D images (128 x 256 x 64 voxels) were obtained using a 3D spin echo pulse sequence. The block diagram of the proposed method for segmentation is shown in Fig.1. Following acquisition and Fourier transform, a 3D median filter was applied to the volume to reduce speckle noise. The average lesion and non-lesion values were computed within a 3 x 3 x 3 neighborhood around two points near the lesion boundary, identified manually. Computation time was decreased by limiting the image analysis to a bounding box specified by the user. The average lesion value at the center of the box was computed, and the center was used as a seed for the 3D region-growing process. The region growing terminated when the growing region encountered an edge. Since the lesions under study displayed inhomogeneities in intensity, the output of the region growing process itself did not accurately describe the actual lesion volume. The output of the 3D region growing approach was tiled, and additional operations, such as contour stitching [5], were required. Since the level set method that followed was expected to correct the volume segmentation in the final stages, the region growing output was then fit to an ellipsoid using eigenanalysis, instead of using the more computationally expensive contour stitching approach. The surface thus generated was used as the zero level set surface for the second stage of the segmentation process. The level set proceeds by updating a level set function in a narrow 3D band of pixels around the active surface. This is known as the narrow band approach [6]. The level set function is $\Phi_{n+1} = \Phi_n + \Delta t\,(K_I\,(\alpha\,(P_a - P_b)\,F0 + \varepsilon\,\kappa)|\nabla\Phi| + F_{ext}\,.\,\nabla\Phi)$ where P_a is the probability of the pixel under test (PUT) being a lesion, and P_b is the probability of the PUT being a non-lesion pixel. The sign of the difference term allows the front to shrink or grow at the PUT. F_0 is the constant adjectival speed term, ε is the restraining factor for the dependence on curvature (κ), and F_{ext} is an external force provided in this case by the gradient vector flow. The image-based speed term K_I was chosen to be $1/(1+|\nabla G|)$ where ∇G is the gradient of the Gaussian blurred image [1]. The speed of the moving surface was locally updated so that it slowed down near edges.

Results Fig. 2 shows the results from 3D region growing alone (left) and using the level set approach on the same cross section (right). The images have been histogram equalized for better display. Fig. 3(a) shows a rectangular region around the lesion across 6 consecutive sections, after 3D median filtering. Fig. 3(b) shows the smoothing factor applied in the level set method corresponding to the sections shown in (a). Fig. 3(c) shows the corresponding GVF fields (magnitude) that were used as an external force in the front evolution. The image has been histogram equalized for display. Fig. 3(d) shows the results of the segmentation on the same part of the volume. The results were generated with α= 2.0, ε = 0.025, Gaussian blur parameter = 2.0, GVF parameter μ = 0.59, number of GVF iterations = 80, number of band iterations for the level set = 30, and median filter size = 3 x 3 x 3.

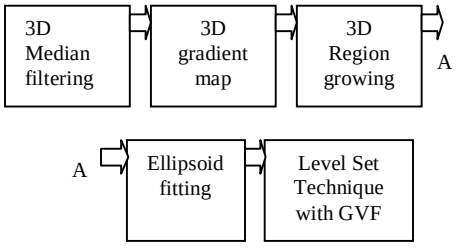


Figure 1: Block diagram

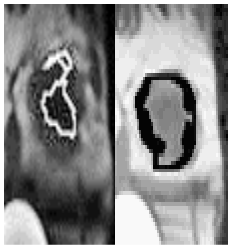
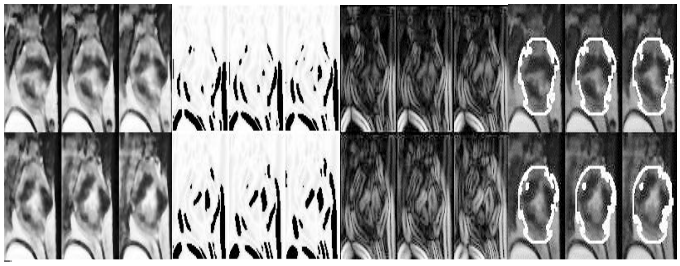


Figure 2: Results from 3D region growing alone (left), and using level sets (right).



(a) (b) (c) (d)

Figure 3: (a) Cross sections of lesion volume, (b) Image based smoothing term K_I, (c) GVF forces, (d) Result of 3D segmentation.

Conclusion A 3D segmentation scheme for lesions with boundary enhancements is presented. The implicit active surface is guided by a combination of forces, including the gradient vector flow and mean curvature, providing a more accurate representation of the lesion boundary than the output of 3D region growing alone. The ellipsoid fitting of the output of the region growing provided the level set method with a surface initialization essential for its propagation. The movement of the front was guided by the local probability of the pixels under test. Results were comparable to those obtained by manually segmenting the lesion volumes.

References

[1] Malladi, R et al., *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 1995, vol. 17, no. 2, pp. 158 – 175. [2] Krishnamurthy, C et al., *IEEE Southwest Symp. on Image Analysis and Interpretation*, 2004, pp. 187– 191. [3] Xu, C et al., *Proc. IEEE Conf. on Computer Vision and Pattern Recognition*, 1997, pp. 66– 71. [4] Ho, S et al., *Proc. IEEE Conf. on Pattern Recognition*, vol. 1, 2002, pp. 532 – 535. [5] Barequet, G et al., *Computer Vision and Image Understanding*, vol. 63, no. 2, 1996, pp. 251– 272. [6] Adalsteinsson, D et al, *J. Comp. Physics*, 118,1995, pp.269-277.