Segmentation of Brain Tissue from MR Images

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Abstract. Segmentation of medical imagery is a challenging problem due to the complexity of the images, as well as to the absence of models of the anatomy that fully capture the possible deformations in each structure. In this paper, we present a method for segmentation of a particularly complex structure, the brain tissue, from MRI. Our method is a combination of three existing techniques from the Computer Vision literature: adaptive segmentation, binary morphology, and active contour models. Each of these techniques has been customized for the problem of brain tissue segmentation from gradient echo images, and the resultant method is more robust than its components. We present the results of a parallel implementation of this method on IBM's supercomputer Power Visualization System for a database of 10 brains each with 256x256x124 voxels.

1 Introduction

We are interested in the problem of segmentation of brain tissue from magnetic resonance images, which is an interesting and important step for many medical imaging applications (see [1] for examples). In this paper, we present a method that is a combination of existing techniques from Computer Vision that have been customized for the task at hand, including a combination of intensity based classifiers, morphological operators and explicit shape constraints.

2 Background

This section presents background on two of the techniques we cascade in our method: *adaptive segmentation* and *deformable contours*. The third technique, *binary morphology* is a standard image processing operation that is discussed in detail in [2].

2.1 Adaptive Segmentation

Adaptive Segmentation is a recently developed, powerful technique for simultaneous tissue classification and gain field estimation in magnetic resonance images [3]. Traditional intensity based segmentation relies on elements of the same tissue type having MR intensities that are clustered around a mean characteristic value, and relies on each cluster being well separated from other tissue clusters. Most MR scanners, however, have inhomogeneities in the imaging equipment, which give rise to a smoothly varying, non-linear gain field. While the human visual system easily compensates for this field, the gain can perturb the intensity distributions, causing them to overlap significantly and thus lead to substantial misclassification in traditional intensity based classification methods.

In Adaptive Segmentation, a Parzen density function is constructed using training points for each of the tissue classes to be identified, and then an algorithm similar to the Estimation-Maximization algorithm is used to iteratively obtain tissue classification and a gain field estimate. A smoothness constraint on the gain field is imposed in the process. By obtaining an estimate of the gain field, the classifier can normalize the intensities to make classification more robust.

2.2 Deformable Contour Models

A deformable contour is a planar curve which has an initial position and an objective function associated with it. A special class of deformable contours called *snakes* was introduced by Witkin, Kass and Terzopoulos [4] in which the initial position is specified interactively by the user and the objective function is referred to as the *energy* of the snake. This energy of the snake (E_{snake}) is expressed as:

$$E_{\text{snake}} = E_{\text{internal}} + E_{\text{external}} \quad . \tag{1}$$

The internal energy term imposes a regularization constraint on the contour as follows:

$$E_{\text{internal}} = \int_s \left(w_1(s)||v'(s)||^2 \;+\; w_2(s)||v''(s)||^2\right) ds \quad , \tag{2}$$

where s is arclength, derivatives are with respect to s, and $v(s)$ stands for the ordered pair $(x(s), y(s))$, which denotes a point along the contour. The choice of w_1 and w_2 reflects the penalty associated with first and second derivatives along the contour respectively.

The external energy term in Equation 1 is responsible for attracting the snake to interesting features in the image. The exact expression for E_{external} depends on the characteristics of the features of interest.

Finding a local minima for E_{snake} from equation 1 corresponds to solving the following Euler-Lagrange equation for v:

$$-\,(w_1 v')' + (w_2 v'')'' + \bigtriangledown E_{\text{external}}(v) = 0 \quad . \tag{3}$$

with boundary conditions specifying if the snake is a closed contour, or the derivatives are discontinuous at the end points. This equation is then written in matrix form as $Av = F$, where $F(v) = -\bigtriangledown E_{\text{external}}$. Here A is a pentadiagonal banded matrix, v is the position vector of the snake, and F is gradient of the external energy of the snake, or the external force acting on it. The evolution equation $\frac{dv}{dt} - Av = F$ is solved to obtain the v that is closest to the initial position. As $\frac{dv}{dt}$ tends to zero, we get a solution to the system $Av = F$.

Formulating this evolution problem using finite differences with time step τ, we obtain a system of the form [5]:

$$(I + \tau A)v^t = v^{t-1} + \tau F(v^{t-1}) \ , \tag{4}$$

where v^t denotes the position vector of the snake at time t, and I is the identity matrix. The system is considered to have reached equilibrium when the difference between v^t and v^{t-1} is below some threshold.

The balloon model for deformable contours is introduces improvements on the snake model [5]. It modifies the the snake energy to include a "balloon" force, which can either be an inflation force, or a deflation force. The external force F is changed to

$$F = k_1 \mathbf{n}(s) + k \frac{\nabla E_{\text{external}}}{||\nabla E_{\text{external}}||} \ , \tag{5}$$

where $\mathbf{n}(s)$ is a unit vector normal to the contour at point $v(s)$, and $|k_1|$ is the amplitude of this normal force.

3 Our Method

We constructed a model for the brain based on expert opinion from Harvard Medical School, and this model is implicit in the segmentation method described below. See [1] for details of the model.

Gain Correction: Initially, we use Adaptive Segmentation to correct for the gain introduced in the data by the imaging equipment. We use a single channel, non-parametric, multi-class implementation of the segmenter that is described in [3]. Training points are used for white matter, grey matter, csf and skin, and therefore the resultant tissue classifications correspond to these four classes. The output of this stage is a set of classified voxels.

Removal of Thin Connectors Using Morphological Operations: We use the following sequence of morphological and connectivity operations to incorporate topological information into the tissue-labeled image obtained from Adaptive Segmentation. First we perform an erosion operation on the input with a spherical structuring element with radius corresponding to the thickness of the connectors between brain and the cranium, so that it eliminates connections from the brain to any misclassified non-brain structure. Then we find the largest connected component with tissue labels corresponding to the brain. And as a third step we dilate the brain component obtained in the previous step by a structuring element comparable in size to the one used in the erosion, conditioned on the brain labels in the input image. This corresponds approximately to restoring the boundary of the brain component that were distorted in the erosion step.

The results of this stage is an improved segmentation of the tissue types, which incorporates topological information, and which has removed some of the artifacts due to pure intensity classification.

Extraction of Brain Surface using Balloon Model: The third step in our segmentation algorithm is the use of a modified balloon model to refine the result of the brain tissue estimate obtained using morphological operations since morphology is often unable to remove all connectors from the brain to the cranium. The intuition behind this step is to incorporate substantial spatial information into the segmentation process via the manual initialization of the brain boundary in a few slices and use that to refine the results obtained thus far. We model the brain surface as a set of adjacent boundary contours for each slice of the scanned volume and use deformable contours to find each of these contours.

We customized the balloon model to exploit the estimate of the brain volume created using the first two steps of our segmentation process. Instead of using a fixed predetermined direction for the balloon force by selecting a sign for the factor k_1 in Equation 5 which is independent of the image characteristics, we define a signed balloon force direction vector, B, with one entry per voxel of the input data. The sign at the i^{th} position of vector B indicates whether the voxel i exerts a force along the inward or outward normal to the evolving contour. This vector B is determined using the brain estimate obtained in the previous morphology step. If voxel i is classified as brain tissue at the end of the morphological routines, then B[i] gets a positive sign, so that the voxel pushes the contour in the direction of the normal towards the boundary of the brain estimate, otherwise B[i] gets a negative sign. The image force is:

$$F = k_1 B(s)\mathbf{n}(s) + k\frac{\nabla E_{\text{external}}}{||\nabla E_{\text{external}}||} \quad , \tag{6}$$

where $B(s)$ is the direction of the balloon force exerted by the image at the point $v(s)$ of the contour, and $\mathbf{n(s)}$ is the normal to the local tangent vector to the contour at s. The unsigned constant k_1 is used to determine the magnitude of the balloon force. This force is used with the same evolution equation as before.

4 Results

We have used our segmentation method to successfully segment several gradient echo data sets. Table 1 quantifies our results for 10 data sets, each of 256x256x124 voxels, by presenting a percentage difference in classification of brain tissue generated by our method when compared with the brain tissue volume generated by an expert on the same data. The validation problem is explored in more detail in [1], [3].

Two views from a 3D reconstruction of the results of our segmenter on a representative data set are shown in the top row of Figure 1, and the same views reconstructed from a manual segmentations for the same data set are shown in the bottom row of the figure.

Case #	1	2	3	4	5	6	7	8	9	10
% Difference	4.6	13.6	10.5	12.3	12.0	0.2	0.5	1.5	2.2	9.6

Table 1. Comparison of Brain Volume with Manual Segmentations

Fig. 1. Results of Our Method (Top Row) vs. Manual Segmentation (Bottom Row)

References

1. T. Kapur. *Segmentation of Brain Tissue from Magnetic Resonance Images*. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA, 1995.
2. J. Serra. *Image Analysis and Mathematical Morphology*. London:Academic, 1982.
3. W. Wells, R. Kikinis, W. Grimson, and F. Jolesz. Statistical Intensity Correction and Segmentation of Magnetic Resonance Image Data. In *Proceedings of the Third Conference on Visualization in Biomedical Computing*. SPIE, 1994. to appear.
4. A. Witkin, M. Kass, and D. Terzopoulos. Snakes: Active contour models. *International Journal of Computer Vision*, 1(4):321–331, june 1988.
5. L. Cohen. On active contour models and balloons. *Computer Vision, Graphics and Image Processing: Image Understanding*, 53(2):211–218, march 1991.