Extracting ICC Surface from an MR Image

T. Kapur *
MIT AI Laboratory NE43-733, 545 Technology Square, Cambridge MA 02139

Abstract

Our goal is to automatically extract the surface of the intra-cranial cavity (ICC) from a magnetic resonance scan of a patient's head. The structures comprising the ICC can vary considerably in shape and in size from one patient to another, making this segmentation task challenging to automate. We discuss the limitations of existing energy minimizing techniques like snakes and balloons with respect to this application, and introduce a radial force based method which has produced promising results.

1 Description of the Problem

The MRI scan of a patient's head is a 3D volume of tissue responses. We treat this volume as a stack of parallel 2D slices where each slice shows a cross-section of the patient's head. The brightness value of a pixel in the scan is a measure of the radio frequency (RF) response of the corresponding scanned region, which, in normal patients, can be one of: brain tissue, cerebro-spinal fluid (csf), meninges (the protective layer surrounding the brain), subcutaneous fat, skin, neck, or air. Of these structures that are visible in the scan, the ICC is defined to include the brain tissue and the csf. Ideally, the RF response of the ICC, and hence the brightness values of corresponding pixels, should be distinguishable from that of the other structures in the head. However, spatial inhomogeneities in the sensitivity of the scanning equipment leads to a gain artifact in the images [3]. Motion artifacts further reduce the quality of the signal. Due to these limitations of the imaging process, structures that are expected to have distinct RF responses may sometimes not be distinguishable in the scan, and structures that are not physically connected in the anatomy may appear to be connected in the scan. In coronal SPGR images, for example, often the meninges appears with the same brightness values as brain tissue, and the neck tissue appears connected to the ICC. Segmenting the ICC from the rest of the scan, therefore, cannot be accomplished as a simple pattern recognition routine. Rather, the mentioned problems make obvious the need for introducing knowledge of the relevant anatomy into the segmentation process.

ICC surfaces have a number of useful applications in segmenting and registering medical imagery of the head. For example, the automated Bayesian tissue classifier developed by Wells [3] to identify the different tissue classes in the brain uses the ICC surface as its input to mask the region in which it operates. Also, methods to identify changes in the brain over time use the ICC as the basis for registering temporal data sets [5] [4]. Current techniques for extracting the ICC generally involve extensive manual intervention which reduces the accuracy, reproducibility and efficiency of the process. By automating the extraction of the ICC, our goals are to improve the effectiveness of subsequent segmentation and registration processes and facilitate automated surface extraction for other anatomical structures. As well, our goal is to evaluate the applicability of the techniques developed for extracting the ICC to other segmentation problems in medical imagery.

2 Snakes and Balloons

We initially explored the classical snake [1] and balloon models [2] of energy minimization. The rest of this section provides some background on snakes and balloons, and discusses our experience with implementing these two models.

2.1 On Snakes

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 Terzopolous in [1] in which the initial position is specified interactively by the user and the objective function is referred to as the *energy* of the snake. By analogy to physical systems, the snake slithers to minimize its energy over time. This energy of the snake (E_{snake}) is divided into two components: the *internal energy* of the snake ($E_{internal}$) and the

*tkapur@ai.mit.edu

external energy of the snake ($E_{external}$). The internal energy term imposes a piecewise smoothness constraint on the snake by preferring low first and second derivatives along the contour, while the external energy term is responsible for attracting the snake to interesting features in the image.

$$E_{snake} = E_{internal} + E_{external}$$

$$E_{internal} = \int_s (w_1(s)||v'(s)||^2 + w_2(s)||v''(s)||^2)ds$$

where s is the parameter of the contour, 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. Choice of w_1 and w_2 reflects the mechanical properties of the snake, since they represent the coefficients of elasticity and rigidity for the contour respectively. It is suggested in [1] that $E_{external}$ can be chosen depending on the characteristics of the features that one aims to extract using snakes. For example, if $E_{external}$ is set to $-||\nabla I(v(s))||^2$, then the snake will be attracted to points of high brightness gradient magnitude in the image.

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

$$-(w_1 v')' + (w_2 v'')'' + \nabla E_{external}(v) = 0$$

with the given boundary conditions.

This equation is then written in matrix form as

$$AV = F$$

using $F(v) = -\nabla E_{external}$. Here A is a pentadiagonal banded matrix, V is the position vector of the snake, and F is the external force acting on it.

The evolution equation: $\frac{dV}{dt} - AV = F$, is solved to find 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 [2]

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

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.

We found that snakes provide a useful framework for extraction of specific features from an image. The internal and external components of the snake energy helped us separate the specifications of the expected shape of the features of interest from specifications of the expected brightness patterns along the features of interest. However, we have not been able to use snakes to extract the boundary of the ICC from MR scans for the following reasons.

As observed in [2], the coefficients of elasticity and rigidity can greatly influence the evolution of the snake over time iterations. Large values (close to 1) for these coefficients lead simply to the smoothing of the initial curve, and the effect of the underlying image, or the external energy is not noticeable. Smaller values reduce the regularization effect, and the evolution is mainly determined by the external energy of the snake.

The snake model allows the elasticity and rigidity coefficients to be constant over time iterations, which means that the same regularization constraint can be applied to all portions of the contour. The model also allows these coefficients to vary over time iterations, which means that different pieces of the contour can obey different regularization constraints.

Clearly, a contour as complex as the boundary of the ICC would be inadequately modeled by constant elasticity and rigidity coefficients. A more accurate model along these lines would probably contain more detailed information about the mechanical properties of the intended contour. However, it is not obvious to us how such a detailed model could be built without finding the ICC boundary in the first place.

To minimize the effect of assuming constant elasticity and rigidity coefficients in our current implementation, we have kept both the coefficients sufficiently low (0.1) so that the regularization effect is negligible compared to the impact of the external energy.

Another reason why we need a richer model than snakes for our application is that the boundary of the ICC is surrounded by points of high brightness gradient (the surrounding matter being soft tissue of the neck or the meninges), which makes insufficient the use of any of the functions suggested in [1] as the external energy terms of the evolution equation.

2.2 On Balloons

The balloon model, as described in [2], builds upon the snake model. It modifies the snake energy to include a normal "balloon" (2D) force. The force F now becomes

$$F = k_1 \mathbf{n}(s) + k\frac{\nabla P}{||\nabla P||}$$

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. Note that in this balloon model, only the direction of the gradient of the external force (∇P) is used, and not its magnitude. This normalization of the external force, along with the constraining of the magnitude of k, are done to avoid instabilities due to time discretization. A more elaborate discussion of this can be found in [2].

The balloon model [2] was appealing to us for two reasons. First, the introduction of the normal force allows the initial position to be significantly far off from the intended contour. And second, changing the sign of k_1 enables the balloon to inflate or deflate from its initial position. Since closed snakes tend to shrink in the absence of external forces, this model gives a contour the additional ability of being able to expand in the absence of external forces.

The balloon model came closer to what we needed, but was still not sufficient for segmenting the ICC for the following reasons. First, tangent discontinuities in the contour (introduced by isolated, usually noisy edge pixels) are not removed by the smoothing terms in our energy function. This is because we need to keep the elasticity and rigidity coefficients fairly low in order to model the nature of the ICC boundary reasonably. Once such a discontinuity occurs, further iterations can cause the contour to cross itself (because of the normal force), which is clearly not desirable behavior in our task. Second, it is not sufficient for us to have a single value as the strength of the normal force acting on the contour over the entire image, because we cannot guarantee that the initial position of the contour will always be completely inside or outside the expected equilibrium position.

3 Our Method

Our algorithm for extracting the surface of the ICC is motivated by the methodology used by experts at the Surgical Planning Lab at Brigham and Women's Hospital to accomplish the same task. We process the scanned volume on a slice-by-slice basis, with some interaction between the slices. We think of our method as operational in "2.5D" since it enforces smoothness of the ICC boundary between adjacent slices, but not any other 3D constraints on the data.

To start the algorithm, we assume as interactive input, the boundary of the ICC marked accurately in one slice of the data set. Then the two parts of our algorithm: estimating the region comprising the ICC in a slice, and then finding the exact contour that corresponds to the boundary of the ICC in that slice, are executed sequentially on each slice of the data set, resulting in the surface of the ICC.

3.1 Estimating the ICC

The following is a summary of the steps used to compute the ICC estimate of a slice (s_1), given the accurate ICC boundary for at least one of its adjacent slices (s_0). First, determine the extreme x and y coordinates of s_0. This defines a rectangular search area for the ICC in s_1. Second, find the range of brightness values of the ICC defined in s_0, and compute connected components in the rectangular search area in s_1 that have brightness values in that range. Third, label the connected components as an estimate of the ICC in s_1.

Using the estimate of the ICC for slice s_1 (which is a region, and not a contour) and the exact boundary of the ICC in s_0 as an initial position, an energy minimization technique is used to compute an exact boundary for the ICC in s_1. Details for the energy minimization technique are given below.

3.2 Energy Minimization

The idea behind the model we are using for extracting the ICC surface is to exploit the information collected in the first part of the algorithm – the part where we construct an estimate of the ICC in a slice. The main feature of the model that is different from the models mentioned above is a radial force that is exerted by each point of the image on the contour. The direction of this radial force is inward (towards the center) for all points that are outside the ICC estimate, and it is outward for all points that are inside the ICC estimate.

The evolution equation for our model is

$$(I_d + \tau A)v^t = v^{t-1} + \tau F(v_{t-1})$$

where $F = k(s)\mathbf{r}(s)$ and $\mathbf{r}(s)$ is a unit vector from point s on the contour to the center of the contour. Motion along $\mathbf{r}(s)$ corresponds to a deflating force applied to the contour at s, and motion in a direction opposite to that of $\mathbf{r}(s)$ corresponds to applying an inflating force to the contour at point s. $k(i)$ is a scalar defined at each point i in the image, and $k(s)r(s)$ is the radial force exerted by the ICC estimate on point s of the contour. The purpose of the k's is to determine whether the force at point s should be towards the center of the contour or away from the center of the contour: if pixel i is outside the ICC, then $k(i) < 0$, else $k(i) > 0$.

4 Results

We have used our algorithm to extract ICC points from five normal data sets of 124 slices each. Sample results for three slices are shown in Figure 1. Each row consists of a pair of images: the left one is a slice from a data set, and right one is a manually created mask for the ICC in that slice. For comparison purposes, we have overlaid (in white) both the original data and the manual segmentation of each pair with the result of our algorithm. Expert visual inspection of our results indicates a good match with the boundary of the manual segmentation of the ICC.

We are currently exploring methods for validating our results. One validation approach is to use manually segmented data sets as the ground truth and use the RMS error between the two sets of boundary

points as a measure of the performance of our algorithm. Another validation approach is to have a second expert (the first being the one who segmented the data set before) decide on the classification of points that our algorithm classifies differently from the manual segmentation.

5 Discussion

A moot issue is whether the problem that we are addressing needs 3D treatment, and a 2.5D approach is inherently insufficient. A 3D version of our algorithm would be a reasonable extension, but our argument for our 2.5D approach is based on how experts appear to accomplish the task. Our observation of experts executing this task was that ambiguities in classification for a slice were resolved by referring to adjacent slices, not the entire rest of the volume. The point can be made however, that interpreting this as an indication that 3D information is not needed for the task is a limitation of our understanding of the expert methodology. Determining whether or not experts use 3D information for this problem may be a little bit harder than actually implementing a 3D version of the algorithm to compare the results with the current implementation, which is what we intend to do in the near future.

6 Acknowledgments

Thanks to Sandy Wells, Eric Grimson, Gil Ettinger and Ron Kikinis for useful discussions. And to Dimitri Terzopoulos for providing code for the "numerical guts" of classical snakes that we used as a base for our experimentation.

References

[1] M. Kass, A. Witkin, D. Terzopoulos, "Snakes: Active Contour Models", *International Journal of Computer Vision*, 1:321-331, 1987.

[2] Laurent Cohen, "On Active Contour Models and Balloons", *Computer Vision, Graphics and Image Processing: Image Understanding*, 53(2):211-218, March 1991.

[3] Wells, W.M., R. Kikinis, F.A. Jolesz, W.E.L. Grimson, "Statistical Gain Correction and Segmentation of Magnetic Resonance Imaging Data", in preparation.

[4] W.E.L. Grimson, T. Lozano-Perez, W.M. Wells III, G.J. Ettinger, S.J. White, R. Kikinis, "An Automatic Registration Method for Frameless Stereotaxy, Image Guided Surgery, and Enhanced Reality Visualization", submitted to IEEE CVPR 1994.

[5] G.J. Ettinger, W.E.L. Grimson, T. Lozano-Perez, W.M. Wells III, S.J. White, R. Kikinis, "Automatic Registration for Multiple Sclerosis Change Detection", submitted to IEEE Workshop on Biomedical Image Analysis 1994.

Figure 1: Results