MACHINE-LEARNED CONTOURS TO ASSIST BOUNDARY TRACING TASKS

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ABSTRACT

Our focus is to assist interactively in the initial segmentation of medical imagery. In near-real-time, from an initial set of pixels traced, our system learns the characteristics of a contour being traced and projects ahead the trace. This paper provides an overview of our approach, presents promising results, and outlines our research directions.

I. INTRODUCTION

Despite the research in edge detection over the past decades, the current state of the practice for delineating regions of interest in medical imagery is an expert's manual outlining of the region. Current techniques often yield too many, unconnected edges, which then still require manual filtering, and this only becomes worse in the presence of noise and texture. Johnson, et.al.,[3] note: *"Although image segmentation and contour/edge detections have been investigated for quite a long time, there is still no algorithm that can automatically find region boundaries perfectly from clinically obtained medical images. There are two reasons for this. One is that most of the image segmentation algorithms are still noise sensitive. The second reason is that most segmentation tasks require certain background knowledge about the region(s) of interest."*

We are working on a new approach, to provide real-time learning and trace-ahead capabilities to assist experts in these tasks. The combination we set forward capitalizes on what each does best: a human expert provides global perspective and context, and a software system quickly analyzes and works through similar local neighborhoods.

II. LEARNING & PROJECTING A TRACE

A model of our interaction scenario is illustrated on an enlarged set of pixels, shown in Figure 1. The darkest pixels represent a contour of 120 pixels. The first 20 pixels on the left were traced manually, moving a cursor over the image.

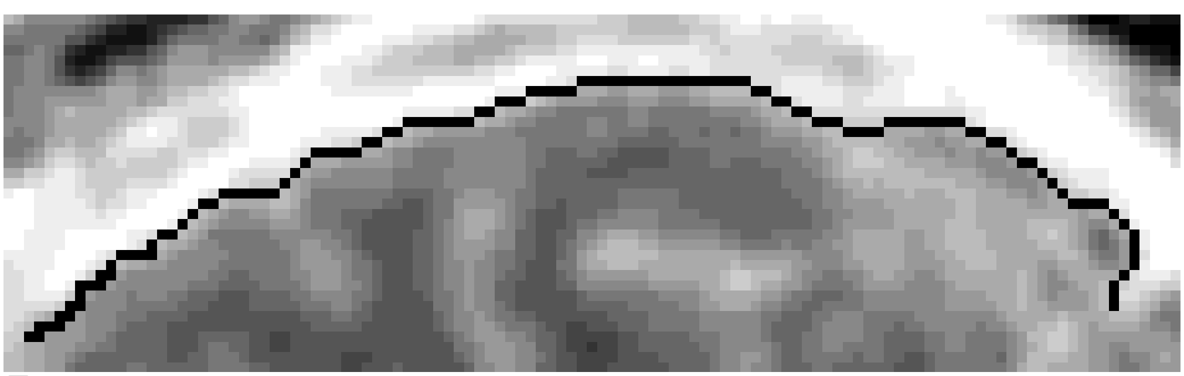

Figure 1 : Enlargement: Network-traced path through the grey-scale landscape.

That segment is used to learn the local landscape, and the system then projects ahead the boundary contour through similar pixel territory. The contour is learned and followed by tracking characteristics of pixels to the left, to the right, and along the directed path.

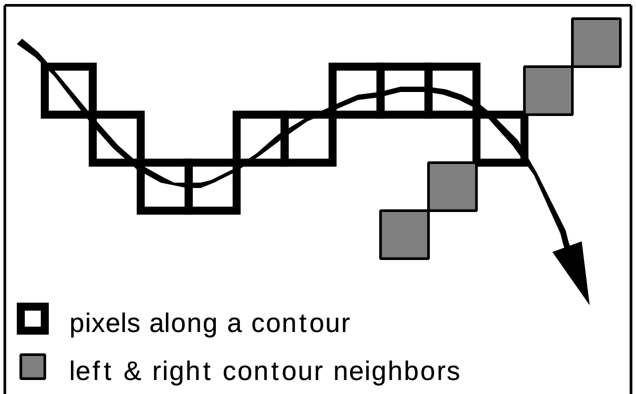

Figure 2: a contour point & its neighbors

B. Interaction of Expert & System

Figure 3 shows some raw MRI data under study at the National Institute of Mental Health [2].

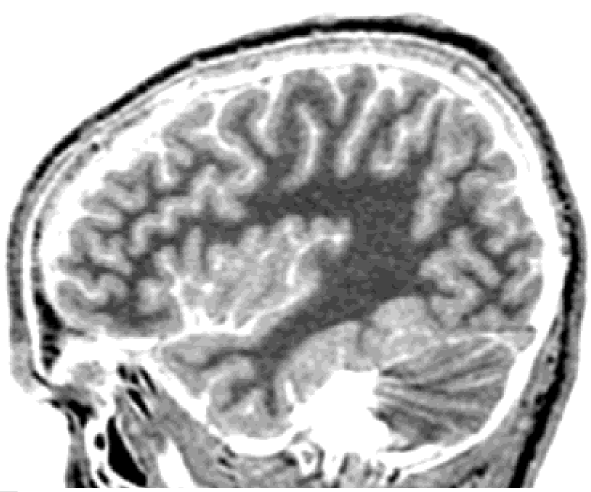

Figure 3 : Raw MRI data

Figure 4 shows the results of our system following the contour it was taught, a contour dividing the white/grey matter in the image. The interaction proceeds through these steps:

1. the analyst starts off by specifying a representative contour, in this case the 40 pixels indicated by the asterisk;

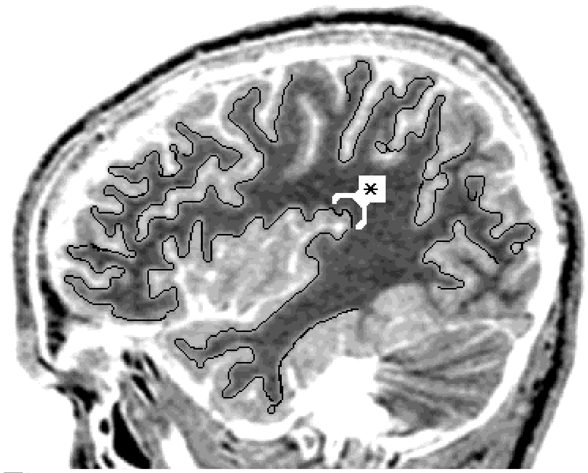

Figure 4 : Grey/White boundary traced automatically; training segment indicated by asterisk (*).

2. the system learns the specifics of the contour;
3. the system extends the path initially begun; the path is extended a pixel at a time, maintaining the initially learned neighborhood characteristics;
4. in a locality unrepresented in the training set, the system may not follow well; the trace will need restarting (but not retraining) outside that locality.

We are using neural networks as the machine learning method since they can map their data to a wide range of (possibly nonlinear) models, are computationally reasonable, are noise and texture resistant, and are well understood as learning systems.

The left half of the Figure 4 shows the network at its best, following the boundary well. On the right half, we can observe the system running into trouble in neighborhoods of the contour unrepresented in the training set.

B. Input Representations

Our first learning models used only raw pixel values as inputs. We experimented with various masks & filters for pre-processing the raw pixel-valued inputs to the network. Using input masks modelled after the visual system (center-surround filters of the retina and gradient filters of V1), both the quality and generality of the learned contour improved [1].

III. DISCUSSION

This approach is guaranteed to produce a continuous, single-pixel wide boundary definition. This system attempts to learn the expert's distinction, rather than following some theoretically defined "best" edge location. For example, on ramp edges, the system learns to follow the ramp according to the initial placement by the expert (possibly to one side of the ramp), rather than at the preordained middle of the ramp, the standard assumption of where an "edge" should be.

For this flexibility, our work stands in contrast to the use snakes [4] or "intelligent scissors" [6] in boundary tasks. In both those approaches, an approximate initial outline or partial trace is specified by an operator, and the system then settles into an equilibrium state defining the boundary more precisely. This final state, though, is still determined to a large degree by ***a priori*** assumptions and definitions of "edge". In our system, an operator also provides initial data, but our system uses that data alone to learn the character of a contour, unclouded by earlier assumptions.

We are funded for 1997-98 through a technology transfer grant, to incorporate this research model into a commercial tracing tool used by Visible Productions, local biomedical image research company. In their imagery database, experts have already defined contours on human cryosection photographs. Using this as our ``ground truth'', we are now studying how close the neural network comes to their delineation, when representative segments are used for training.

ACKNOWLEDGEMENTS

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REFERENCES

[1] S.Crawford-Hines & C.Anderson, "Neural Nets Facilitate Boundary Tracing Tasks in Medical Images", *Neural Networks for Signal Processing VII (Proceedings of the 1997 IEEE Workshop)*, 1997, pp. 207-215.

[2] Hyde, Stacey, Coppola, Handel, Rickler, & Weinberger, "Cerebral morphometric abnormalities in Tourette's syndrome: a quantitative MRI study of monozygotic twins", *Neurology*, 1995; 45:1176-82.

[3] C.Johnson, R.MacLeod, & J.Schmidt, "Software Tools for Modeling, Computation, and Visualization in Medicine", *CompMed 94 Proceedings*, World Scientific, 1995.

[4] M.Kass, A.Witkin, & D.Terzopoulos, "Snakes: Active Contour Models", *First International Conference on Computer Vision*, 1987, pp.259-268.

[5] J.Malik & P.Perona, "Finding Boundaries in Images", *Neural Networks for Perception*, Academic Press, 1992, pp.315-344.

[6] E.N.Mortensen and W.A.Barrett, Intelligent Scissors for Image Composition, *Computer Graphics (Proceedings of SIGGRAPH'95)*, ACM, 1995, pp.191-198.

[7] M.Ozkan, B.Dawant, & R.Maciunas, "Neural-Network-Based Segmentation of Multi-Modal Medical Images: A Comparative and Prospective Study", *IEEE Transactions on Medical Imaging*, v.12, #3, 1993, pp.534-554.