An Edge Based Image Segmentation Method

M. W. Dow[1], R. L. Nunnally[2]

[1]Robert and Beverly Lewis Center for Neuroimaging, University of Oregon, Eugene, Oregon, United States, [2]Robert and Beverly Lewis Center for Neuroimaging, University of Oregon, Eugene, OR, United States

Introduction

We implemented a 2-D edge definition that satisfies our goals of providing accurate and contiguous estimates of tissue boundaries in MR images using algorithms that do not require thresholds that are image or image modality dependant, and using algorithms that can be extended to 3-D for segmentation and feature extraction, such as landmark identification tasks. The approach uses an edge detection algorithm adaptive to local image characteristics for determination of an optimal spatial scale to maintain continuity in the presence of noise. All resulting edges are linked to form an over-segmented image. Simple similarity rules for combining sub-regions are used to form a binary tree of sub-regions. Manual review or semi-automated tools can then be used to select the region of interest.

Methods

The edge definition we use can be summarized as i) The gradient magnitude is a local maximum in the direction of the gradient, and ii) A normalized measure of edge strength, the gradient magnitude weighted by the scale, is locally maximum over scales. This definition is unbiased, in the sense that it is not parameterized for particular applications.

The edge detection algorithm locates and follows edge segments, across the image and across scales, using a large set of oriented Difference of Gaussian (DoG) filters to estimate derivative directions and maxima. Maxima are estimated by zero-crossings of second order derivative estimates. The filters operate on a small set of scale space sample planes, each convolved with a Gaussian filter with a width σ_p. The first order DoG filters are of the form:

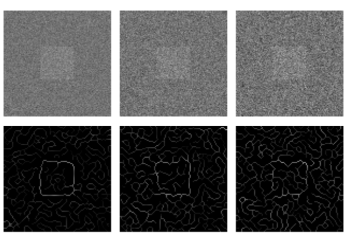
$$G_{(r)} = k\left(e^{-(r-\Delta t/2)^2/\sigma_f^{\,2}} - e^{-(r+\Delta t/2)^2/\sigma_f^{\,2}}\right) \quad , \qquad \Delta t^2 = \sigma_p^{\,2} + \sigma_f^{\,2}$$

where Δt is the width of the filter and *k* is a normalization constant. The standard deviation of the DoG filters, σ_f, and the Gaussian filter used to generate the scale space sample plane, σ_p, are scaled to match the width of the filter. These Difference of Gaussian filters mimic derivative of Gaussian operations at intermediate scales providing continuity of derivative estimates across scales and across space. This derivative estimation method is designed to minimize resource requirements while maintaining smoothness across scale-space.

The derived edges are linked by extending dangling edges in the direction of maximal gradient until an edge intersection is reached. Each elemental region enclosed by edges is then characterized by the average value of the central area, and the average gradient between adjacent regions. The elemental regions are then iteratively combined, forming a hierarchy of sub-regions. The neighboring sub-regions with the smallest difference of average separating edge gradient and average intensity are combined first, and the average characteristics are recalculated for the new sub-region. For specific applications this combination rule can be extended to include any function of edge length, edge scale, absolute region intensity, location within the image, shape characteristics of the bounding edges or sub-regions, or other image based metric.

Results

Testing on images with a range of characteristics demonstrates the robustness of these algorithms. Fig. 1 demonstrates the degradation in detected edges of an intensity step as noise is added. Most of the highest gradient edge segments are clustered around the corresponding step edge location, even with large amounts of noise relative to the step intensity. Note that all points satisfying the edge definition are included, most of which are due to random clumps of noise. The edges are highly continuous as a consequence of the edge definition and the fact that even very low gradient edges are included.



a b c

Figure 1. Intensity step with added Gaussian noise (top), and all detected edges with intensity scaled by relative gradient (bottom). The noise variance is σ^2 =.4, .6, and .8 (left to right).

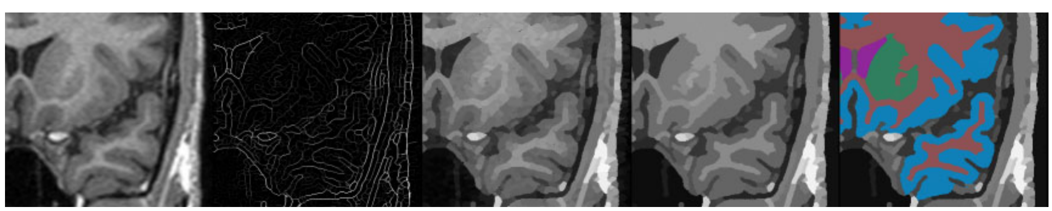


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Figure 2. Segmentation steps. Portion of original image (a), a T1 weighted MRI slice (1 x 1 x 1 mm). Edge map (b) scaled by relative gradient, over-segmented image (c) with each element colored by its average value, one level of the sub-region hierarchy (d) formed by combining similar elemental sub-regions, and the desired regions of interest (e) manually selected from these sub-regions.

Discussion

As edge detection is insensitive to absolute intensity, the method is relatively insensitive to low spatial frequency image intensity inhomogeneities. As no assumptions are made about image content, the method can be applied to a variety of image segmentation tasks, with some flexibility as to rules for combining and selecting sub-regions based on a priori information. Where there is no edge information (second derivative zero crossings) separating regions of interest, the method will fail, and manual or other methods are needed to augment a segmentation. The method is processor intensive, primarily due to the large support derivative estimate filters needed to preserve edge continuity.