Simple, Accurate, Whole-Brain White Matter Segmentation in 3 Seconds

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Introduction

Segmentation of brain white matter could aid assessment of neurological disorders. However, this is not routinely performed in clinical settings, due in part to long computation times and the need for users to carefully tune multiple algorithm parameters to achieve acceptable results. Our goal is to develop a simple, rapid, reliable and accurate technique to segment brain white matter, gray matter and ventricles. We are extending the new parallel level set algorithm proposed by Roberts et. al. [1]. This algorithm efficiently leverages the massive parallelism of commodity graphical processing units (GPUs) to achieve a 14x speed over previous parallel algorithms. Despite this speed advantage, the user is still required to place an initial seed and then tune three parameters to achieve acceptable results. The tuning process requires expertise and increases segmentation time, variability, and inconvenience. Here we report on efforts to automatically select optimal values for the three algorithm parameters when segmenting brain white matter in T1-weighted MR exams.

Methods

The level set algorithm advances the boundaries of the region of interest (ROI) along the local surface norm. Growth is encouraged for similar intensity neighborhoods and penalized for increases in surface curvature. Previous approaches [1] require window and level input parameters to define 'similar intensities'. Instead, we perform k-nearest neighbor classification on the user's seed voxels to define 'similar intensities'. We have also eliminated the need for the user to tune the relative penalty for intensity deviations and curvature increases. This was accomplished specifically for white matter based on a novel, empirical relationship between accuracy, noise, and the curvature weighting parameter (α). *Experimental design*: We performed white matter segmentation on synthetic MRI brain phantoms generated from the BrainWeb Simulated Brain Database [2] (classification of each voxel is known). We tested on six noise levels (SNR = ∞, 100, 33, 20, 14, 11), used eight sets of seed points, and sixteen α values ranging from 0 to 3.0 (step-size of 0.02). In total 768 white matter segmentations were performed. For all segmentations, accuracy was evaluated by computing Dice's coefficient (Dice).

Results & Discussion

Figure 1 shows a surface plot of Dice's coefficient for all the segmentations performed; the empirical relationship between α and image noise level was defined using this surface. The optimal curvature and associated Dice's coefficient for each noise level are reported in Table 1. Importantly, the optimal curvature varies with noise (lower curvature penalties for higher noise levels) but is relatively constant across variations in seed points. Furthermore, the accuracy plateau is quite flat (the optimal curvature weight is one point in a range of acceptable values). Figure 2 shows our minimal input algorithm volumetric white matter segmentation results.

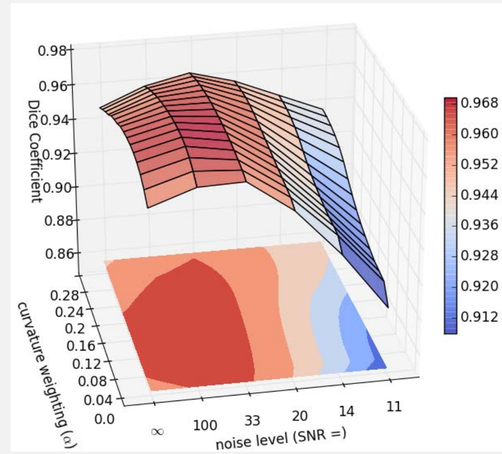

Figure 1 The relationship between accuracy (Dice's coefficient, 1 is perfect), SNR, and level set curvature, from 768 white matter segmentations of BrainWeb T1-weighted MR phantoms.

SNR	100	33	20	14	11
Max. Dice	0.9712	0.9674	0.9550	0.9419	0.9310
α	0.08	0.12	0.22	0.28	0.3

Table 1 The maximum Dice and corresponding α for each SNR value tested. The optimal α increases as SNR decreases.

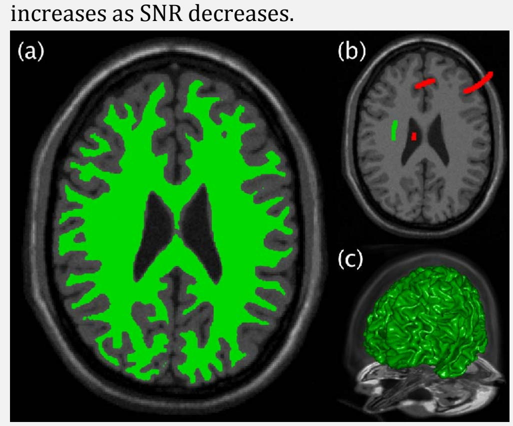

Figure 2 (a) 2D visualization of white matter segmentation results using our algorithm (SNR=33, α=0.12, Dice=0.97). (b) The initial seed voxels (green for foreground; red for background). (c) The final 3D view. Total volume segmentation time: 3 seconds (NVIDIA GTX Titan GPU).

Reference

[1] Roberts, M.,et.al. (2010). *Proc. Conf. on High Performance Graphics* pp.123–132. [2] R.K.-S. Kwan, et.al (1999) IEEE TMI. 18(11):1085-97.