Segmentation Priors From Local Image Properties, Not Location-Based Templates

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Introduction: Tissue class segmentation is integral to many MRI analyses. The process is complicated by noise, scan gain parameters, and bias field. Modern segmentation approaches rely on location-based tissue class prior probability maps to estimate bias field and segment the brain, thereby necessitating an accurate spatial registration of the observed image to the template image of the priors' space. The interdependence of segmentation, registration, and bias correction results in an optimization problem with a large number of parameters best handled in a unified model [1]. Here we describe a novel approach for creating tissue prior maps that offers many advantages over current location-based templates. We propose to gain information about a voxel's tissue type by examining at each voxel the 3D texture of the image over multiple spatial scales, and comparing it to textures from a training set. This collection of texture information over spatial scales is termed a voxel's signature. We hypothesize that voxels of different tissue types can be differentiated on the basis of their signatures, at least as well as location-based spatial priors can do.

Methods: Each voxel's signature was formed as a collection of three statistics (median, Median Absolute Deviation, and Pearson's 2nd skewness coefficient) computed over voxels inside balls of radii from 1 to 19mm. Assuming that bias field is approximately constant over the largest radius, it is straightforward to show that skew statistics are independent of bias field, and that median and MAD are approximately independent of bias field if detrended and scaled by MAD estimated at the largest spatial scale of 19mm. We tested our approach using the publicly available IBSR dataset of T1-weighted MRI volumes, and their manual segmentations [2]. The volumes were from 18 subjects (4 females, 14 males) , with subject ages ranging from juvenile (< 8) to 71 years and voxel resolution approx. 1x1x1.5mm. For each tissue class, a randomly selected training sample of 300 (~ 0.3% of voxels in dataset) signatures was taken from three (s05, s11, and s14) of the 18 subjects. We used libSVM [3] to carry out SVM training and testing on all 18 volumes, and on a version of the same datasets with additional 80% bias field modeled with third order Legendre polynomials. To compare the performance of location-based and signature-based priors, we create priors-only segmentations by assigning to each voxel the class with the highest prior probability and compared them to the manual segmentation with the Dice coefficient. We used non-linear registration to bring the anatomical template of location-based priors distributed with FSL [4] in registration with each of the anatomical volumes. No registration was necessary for signature-based priors as they are generated in subject space.

Results: Figure 1 shows a sample set of priors for one subject. Note how signature based priors are more faithful to the anatomy despite being derived from statistics covering multi voxel neighborhoods. Figure 2 shows Dice coefficients of priors-only-based classification. For all three tissue classes and most subjects, signature-based priors were superior to location-based ones, particularly for white matter whose Dice coefficients rose considerably ($p<0.01$) with signature-based priors. The addition of 80% bias field had little effect on the performance of signature based priors. We emphasize that the priors-only classification is meant to illustrate the improvement of signature-based priors compared to location-based ones, not as an end result of segmentation.

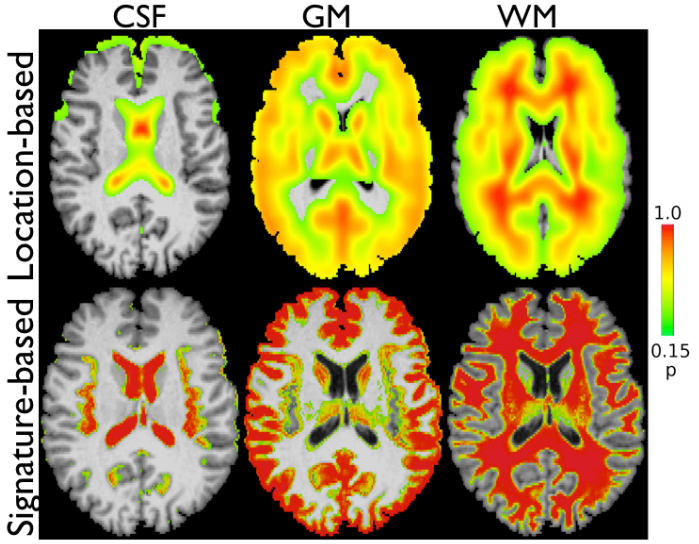

Figure 1: Prior probability maps from subject 9 for each of the three classes with $p<0.15$ masked to show the anatomy. Row 1 shows location-based priors non-linearly registered to the anatomy. Row 2 shows signature-based priors.

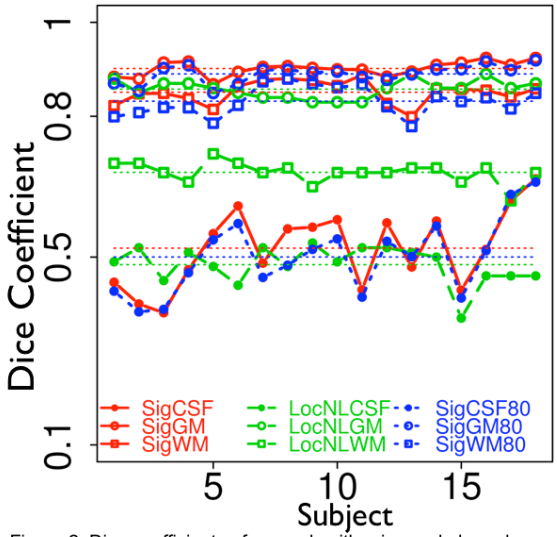

Figure 2: Dice coefficients of manual- with priors-only-based segmentation. Red and blue traces are for signature-based priors with 0 and 80% added bias field, respectively. Dot, circle, and square symbols are for CSF, GM, and WM tissues, respectively.

Conclusions: Our novel approach incorporates prior knowledge about tissue classes that is independent of volume orientation, voxel position, and largely insensitive to bias fields. The prior information is generated from variations in image texture statistics as a function of spatial scale, and a SVM approach is used to associate signatures with tissue types. Signature-based priors are simple to compute, and can replace location-based priors in segmentation, obviating the need for population-derived location-based priors, registration to template space, and explicit bias field modeling.

References: [1] Ashburner and Friston, Neuroimage 2005, [2] http://www.cma.mgh.harvard.edu/ibsr, [3] Chang and Lin, 2001, [4]FMRIB Software Library, Oxford, UK