Framework for Generating Class Priors From Multi-Contrast Images Without Group Volume Templates

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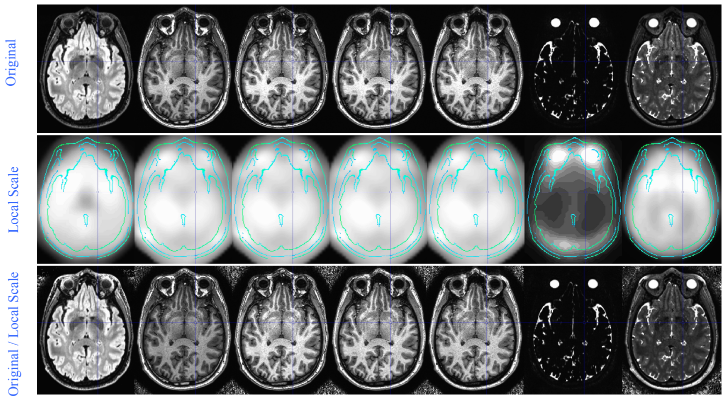
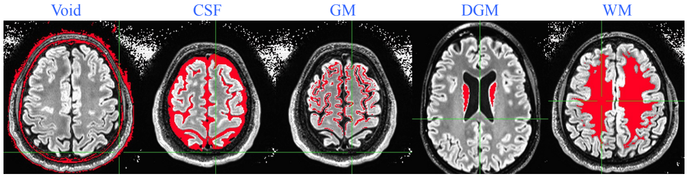
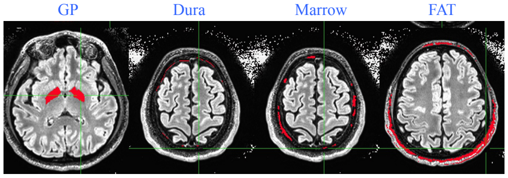
Multi-Contrast Images



Images were affine registered to the corresponding MPRAGE. To reduce the effect of field bias and make features comparable across subjects, we used a local scaling approach: the signal at voxel k is divided by the 90% percentile intensity in a 25 mm radius sphere, a variant of the approach in [8] (For BFWI and FSE T2 images, scaling was by the 65% percentile). Local Scale images were computed with AFNI's 3dLocalstat

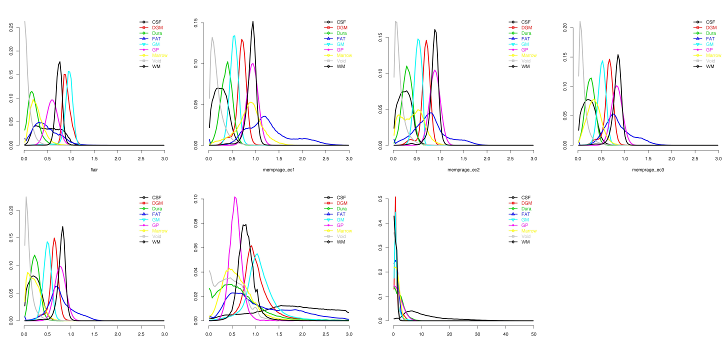
Training Set





ROI masks, some hand drawn, to bootstrap classification classes overlaid on FLAIR image. Form left to right, top to bottom: Void (cortical bone, sinuses, and background), CSF, Gray Matter (GM), Deep GM (DGM), White Matter (WM), Dura, Globus Pallidus (GP), Marrow, and Fat.

$p(a_u|v)$



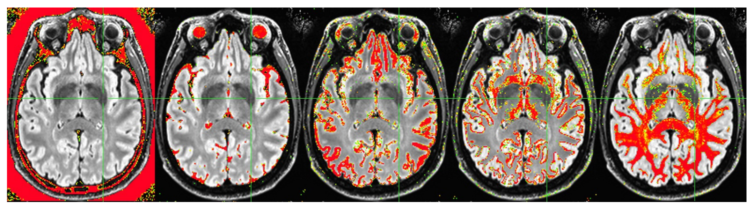
Features and ROIs were then passed to AFNI's [9] 3dGenFeatureDist to create for each feature-class pair a histogram that is used to model the PDF: $p(a_u|v)$ where a_u is the value of feature u, and v is one of the classes..

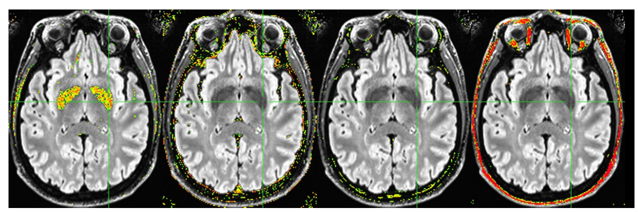
Class Probabilities

$$p(v|a_u)=\frac{p(v)\,p(a_u|v)}{\sum_{w=1}^{k} p(w)\,p(a_u|w)} \qquad p(v|A)=\prod_{u=1}^{c} p(v|a_u)$$

Classification priors were generated with AFNI's 3dGenPriors, which uses a naïve Bayes model with uniform mixing fractions to classify voxels based on the multivariate feature set alone. A is the set of all features.

Likelihoods





Segmentation prior likelihoods for subject whose data was not used in the training set. Color overlay indicates likelihood of class membership given all the features, thresholded at 0.5 to show the underlying anatomy for reference.

Results

Classes such as Void, CSF, GM, and WM are well identified

Less so for remaining classes such as GP, Dura, Marrow, and Fat
- Crude masks used to bootstrap these classes
+ Improving training set is a matter of effort and time
- Approximate correction for the bias field by local scaling
+Improved field bias correction with initial MPRAGE segmentation

We generated membership priors solely derived from the MRI feature set

Priors as first step in an optimization procedure for final segmentation
Method require no group templates or group atlases
Spatial registration needed only within subjects

See Poster#4024 for clinical data application

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