Improved Hippocampal Segmentation by Learning Optimal Weights in Local Multi-Atlas Fusion

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Introduction

- Automated hippocampus segmentation in T1 MRI
  - Applications in computational neuroanatomy
- Multi-atlas segmentation fusion
  - Good performance, but sensitive to atlas selection
  - Majority voting weights each atlas equally
- Recent work chose weights as local estimates of registration accuracy [1,2,3,4]
- We use supervised learning to find the optimal weights based on local registration accuracy

Dataset

- 69 subjects (age 44-48) from PATH Through Life
  - T1 and manual hippocampus tracings [5]
  - N=9 atlas, M=30 training, and T=30 testing

Atlas-based Segmentation

- FS+LDDMM [6] on each subject with all 9 atlases
  - Diffeomorphic registration on sub-region MRI
  - Initializes registration using FS segmentations
- Local registration accuracy (γ) estimated using reciprocal of post-registration mean-squared error

Segmentation Spatial Normalization

- The subject segmentations and registration accuracy maps spatially normalized to a common space (atlas subject 1)
  - Allow for spatially local learning across subjects
  - Affine registration between the corresponding hippocampal shapes
- Sub-regions containing the hippocampus plus a 10 voxel boundary were extracted

"Weight Learning" Linear Regression

- L2-regularized linear regression performed at each voxel
  - Determines optimal atlas weights for the training set

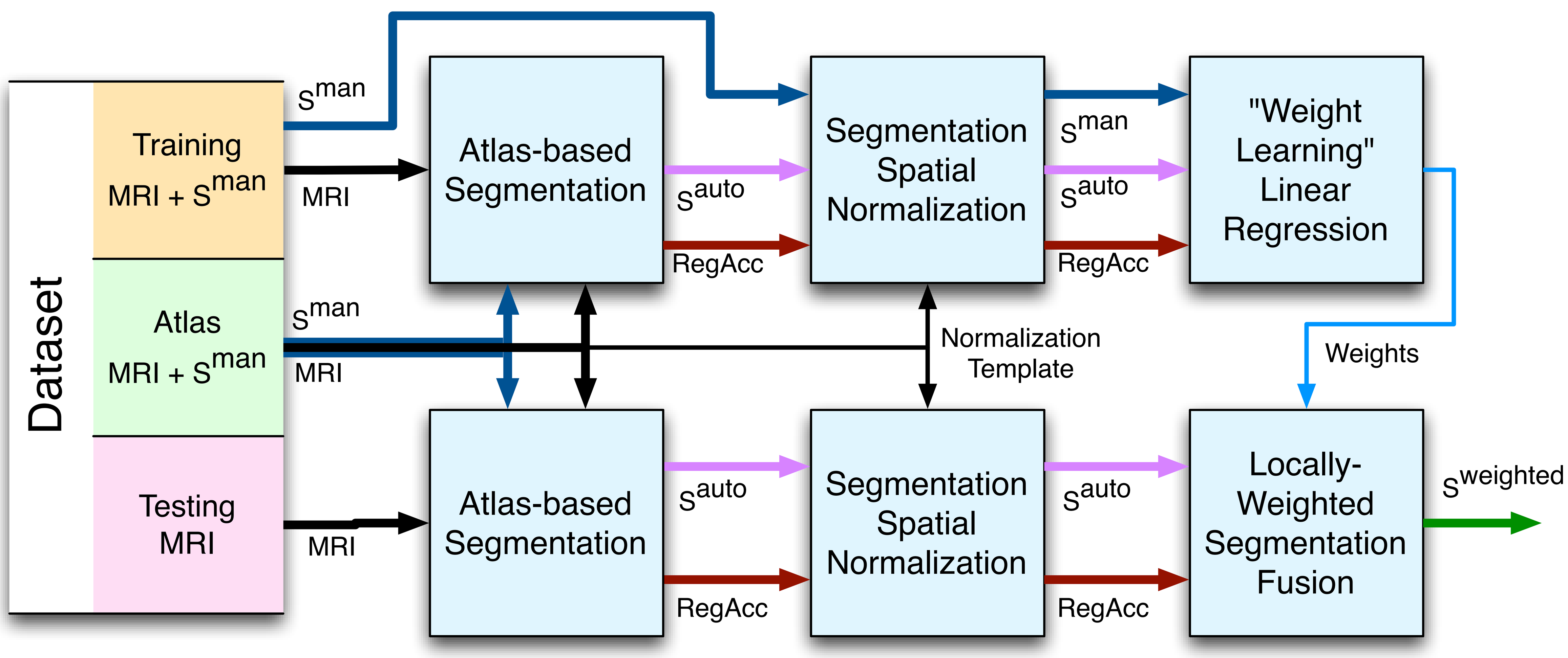
Dependent variable: Manual segmentation
Independent variables: Atlas-based seg × Reg. accuracy
Regression coefficients: Atlas weights

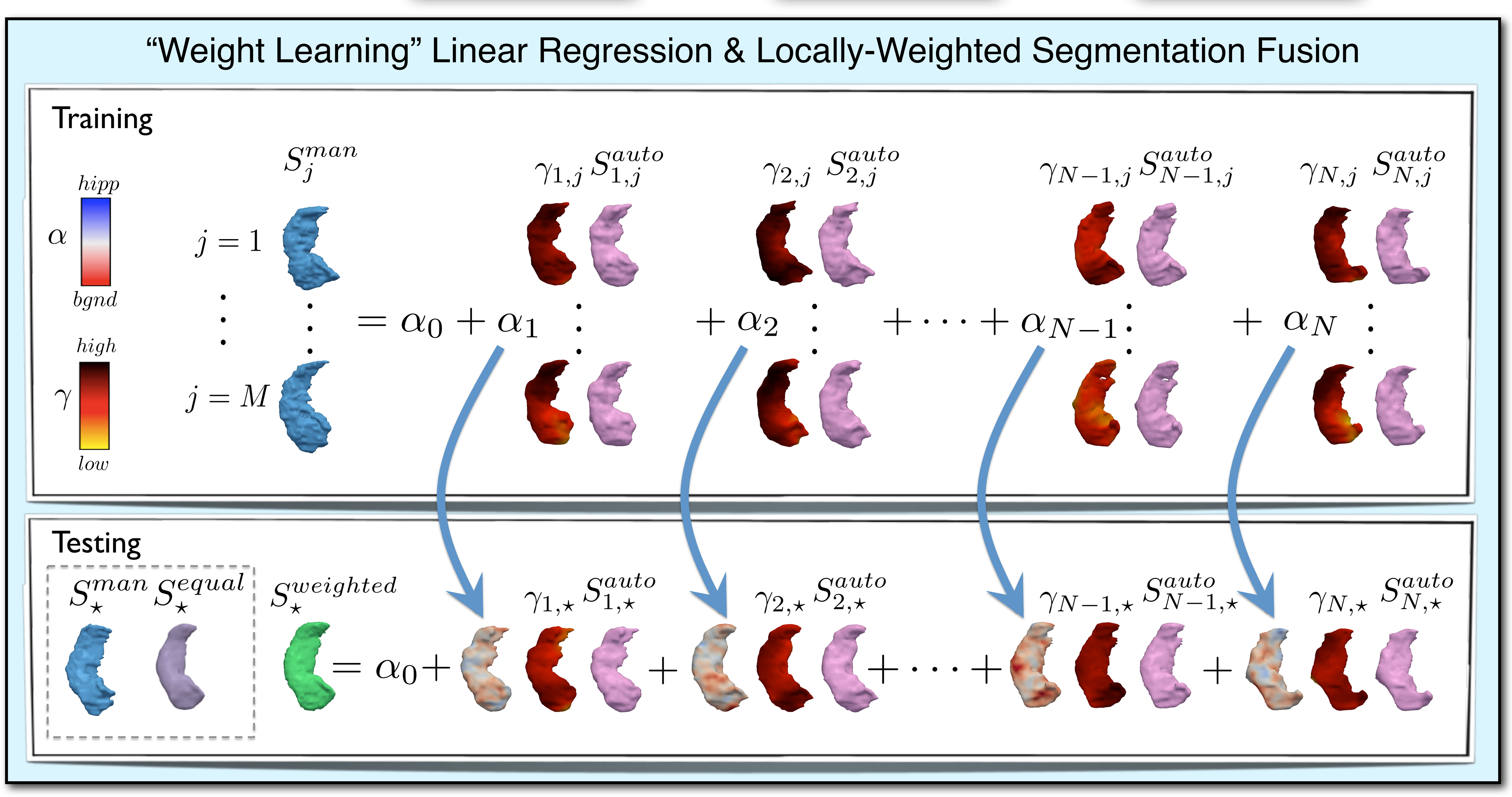
$$S_j^{man} = \alpha_0 + \sum_{i=1}^{N} \alpha_i \gamma_{i,j} S_{i,j}^{auto}$$

Weighted Segmentation Fusion

- Optimal weights used with test set registration accuracy and atlas-based segmentations

$$S_\star^{weighted} = \alpha_0 + \sum_{i=1}^{N} \alpha_i \gamma_{i,\star} S_{i,\star}^{auto}$$





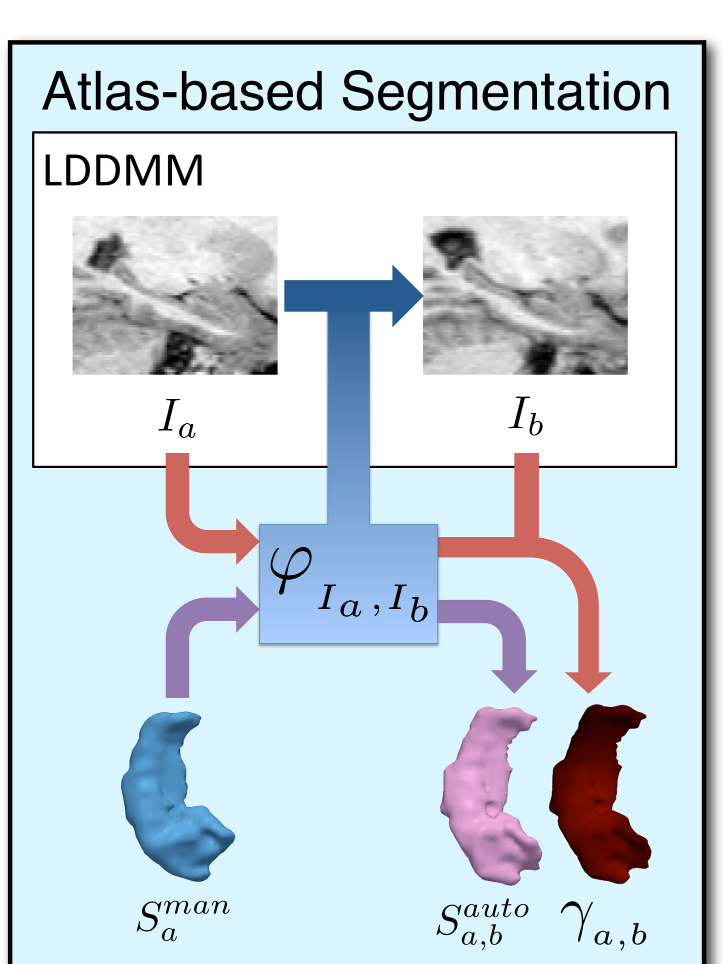
Results

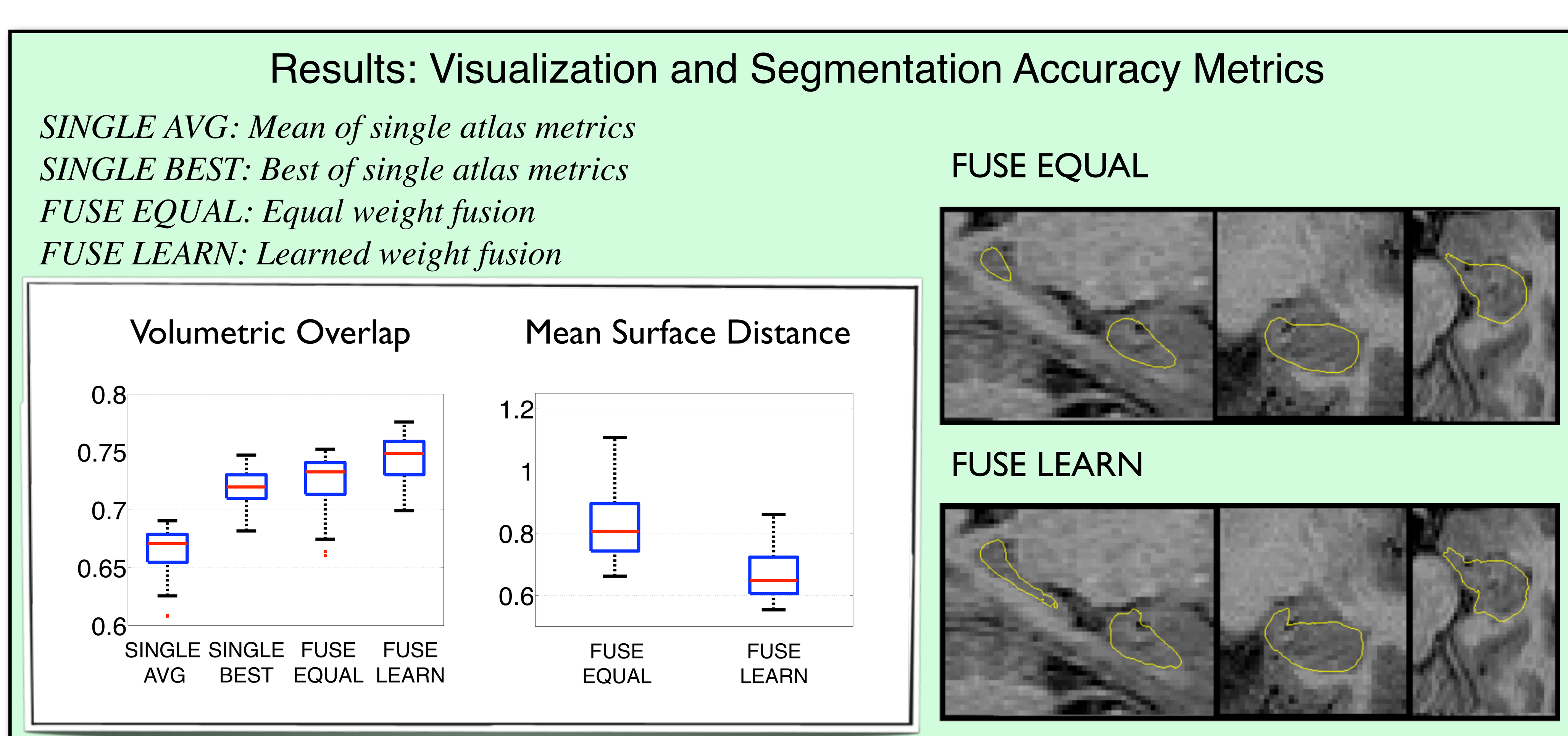
Visual contour comparison

- Learned weights adheres to anatomical boundaries better than equal weights
  - Supervised learning enforces fused segmentations to be more similar to manual segmentations than equally weighted fusion

Quantitative comparison

- Volumetric overlap
  - Union overlap: ratio of intersection to union between manual and automated segmentations
  - Learned vs equal weight segs (t-test, p-value=1.7e-8)
- Mean surface distance
  - Average of minimum distances from auto seg surface to manual
  - Learned vs equal weight segs (t-test, p-value=2.5e-15)





Discussion & Conclusions

+ Learning optimal weights significantly improves automated hippocampal segmentation over the equal weighted approach
– Relies on large training set (30 subjects) to estimate weights

- Future work
  - Effect of training dataset size?
  - Additional subcortical structures
  - Inclusion of demographics, shape similarity as predictors
  - Application to computational neuroanatomy analysis pipelines

References

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