Using Automatic HARDI Feature Selection, Registration, and Atlas Building to Characterize the Neuroanatomy of Aβ Pathology

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Background and Motivation

- **Challenge:** The development of Alzheimer's Disease (AD) is known to be associated with build up of beta-amyloid (Aβ) pathology (detected by PET) as well as neurodegeneration of fibers in the white matter (WM) (detected by HARDI). However the relationship between Aβ pathology and changes in neuroanatomy are unknown.
- **Goal:** To identify which HARDI features may be best suited to reveal significant differences between Aβ- (healthy) and Aβ+ pathologies to better understand the relationship between Aβ build up and changes in neuroanatomy during AD progression.
- **Prior Work:** Register subject data to a common atlas, extract simple features in registered space, and use them to train a classifier.
- **Question 1:** At what stage of HARDI pipeline (DWI, diffusivity estimation, or feature extraction) should registration and atlas building be done to optimize feature analysis and processing?
- **Question 2:** How should the most biologically informative features be selected?

Contribution

- We present an automatic HARDI feature selection, registration, and atlas building framework with the following key advantages:
  - Automatically selects anatomically informative features driven by registration.
  - Preserves and optimizes feature data throughout HARDI processing pipeline.
  - Bypasses the need for re-orientation and re-estimation of diffusion data in atlas space.
  - Generalizes to features from any signal reconstruction and diffusion estimation models.
  - Constructs novel feature atlases.

Method

- The proposed approach extends a Bayesian atlas building algorithm [1] to multiple channels and iteratively updates feature channel weights from the error of the registration to the current template which are then used to update feature atlases. In this way, important features are simultaneously selected while driving registration and atlas building.

Start : $\{W_c^{(0)}\} = 1, \text{Atlas}^{(0)} = \text{Subject}_i,\ \text{Features } c = \{4, 10, 12, 27\}$

1. Register Subjects to Current Atlas with Current Weights

$$\text{mcLDDMM}\{W_c^{(k)}\} = \theta_i^{(k)}$$

Subject_i → $\text{Atlas}^{(k)}$

2. Take Average of Subjects in Atlas Space

$$\frac{1}{N}\sum_i \text{Subject}_i \circ \theta_i^{(k)} \rightarrow \text{Average}^{(k)}$$

3. Calculate Error of Registration to Estimate New Weights

$$\frac{1}{N}\sum_i ||\text{Subject}_i \circ \theta_i^{(k)} - \text{Atlas}^{(k)}|| \rightarrow \{W_c^{(k+1)}\}$$

4. With Updated Weights and Average, Create New Atlas

$$\text{mcLDDMM}\{W_c^{(k+1)}\} = \mu^{(k+1)}$$

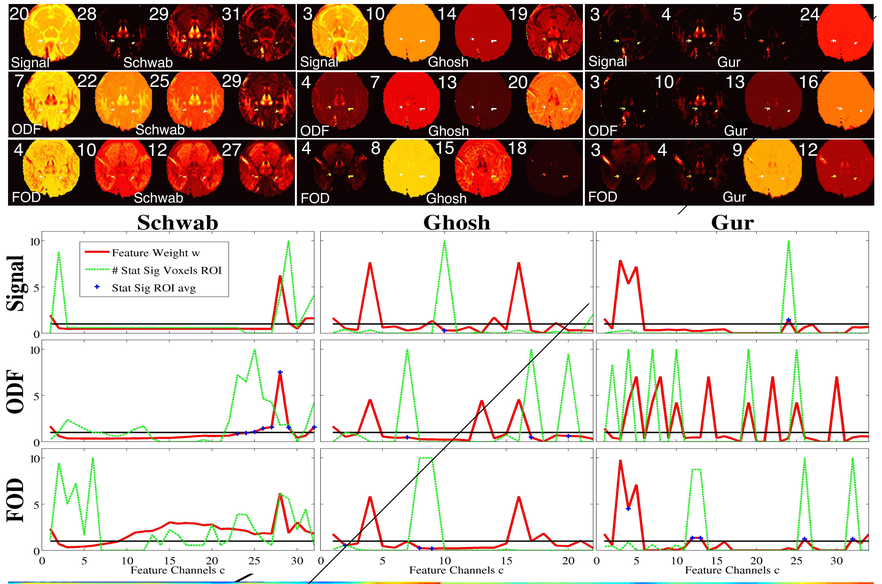
$\text{Atlas}^{(0)}$ → $\text{Average}^{(k)}$

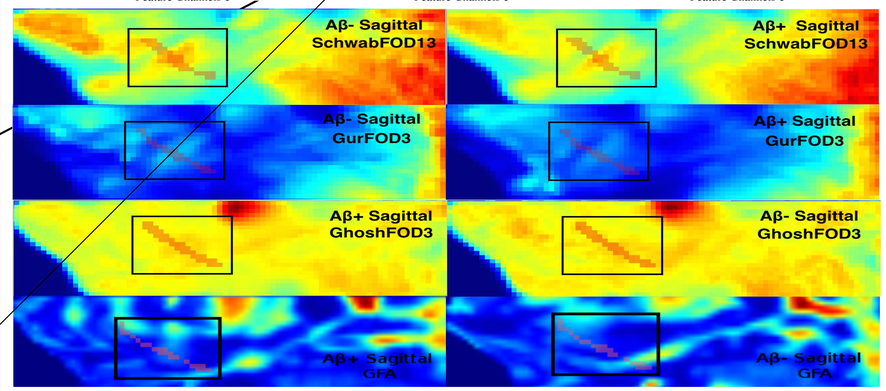
$\text{Atlas}^{(0)} \circ \mu^{(k+1)} \rightarrow \text{Atlas}^{(k+1)}$

End : $\{W_c^{(K)}\},\ \text{Atlas}^{(K)}$

Results

- **Data:** 15 Aβ- and 17 Aβ+ subjects from HCP each with HARDI scans with 128 DWI.
- **Features:** 30 features from Schwab [2], 20 features from Ghosh [3], and 32 features from Gur [4].
- **ROI:** The parahippocampal WM region is shown to undergo fiber degradation in aging and MCI.
- **Aim:** Find selected features that show fiber degradation between Aβ- and Aβ+ populations in ROI.





- **Top:** Visualization of a subset of features extracted from raw HARDI signal, the orientation distribution functions (ODF), and fiber orientation distribution (FOD) for each feature extraction framework.
- **Middle:** Results of proposed feature selection method with feature weights (red) compared to proportion of statistically significant voxels (green/blue) in ROI between Aβ- and Aβ+. Important features have weights > 1 (black line).
- **Bottom:** Comparison of registered feature maps for Aβ- and Aβ+ populations within ROI (segmentation from top left to bottom right in bounding box) showing statistically significant decreases in feature values intersecting ROI for Aβ+.

Conclusion

- With our automatic HARDI feature selection, registration, and atlas building algorithm, we have shown that some of the features important for registration (high weights) may be useful for Aβ classification by showing patterns of statistically significant differences within ROI (Middle). We have found that the presence of Aβ pathology may be associated with decreases in selected HARDI features (Bottom) which may indicate neurodegeneration. Future work will be to integrate classification within our framework.

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