Rotation Invariant Features for HARDI

Evan Schwab[1], H. Ertan Çetingül[3], Bijan Afsari[1], Michael A. Yassa[2], and René Vidal[1]
[1]Center for Imaging Science, Johns Hopkins University, Baltimore, MD
[2]Department of Psychological and Brain Sciences, Johns Hopkins University, Baltimore, MD
[3]Imaging and Computer Vision TF, Siemens Corporation, Corporate Technology, Princeton, NJ

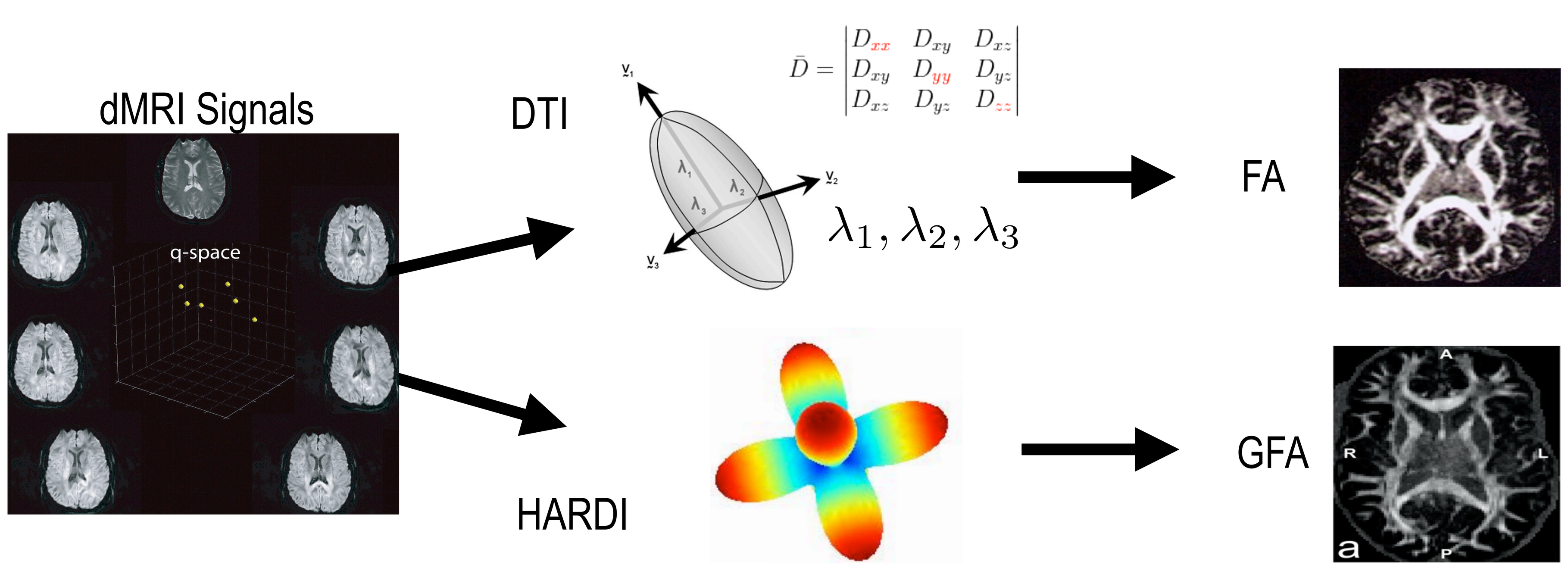
Motivation and Background

Diffusion MRI (dMRI) is a non-invasive imaging technique used to model neuronal fibers in the brain in order to characterize the white matter architecture of normal and diseased patients.

Extracting scalar features from this high-dimensional data is important to develop biomarkers that aid in the classification of neurological diseases.

For diffusion tensor imaging (DTI) the most widely used feature is fractional anisotropy (FA) which measures the level of anisotropy of a tensor from [0,1]. In the case of high angular diffusion imaging (HARDI), most utilize the FA generalization, known as generalized fractional anisotropy (GFA).

However, these scalar features discard too much information in dMRI data.



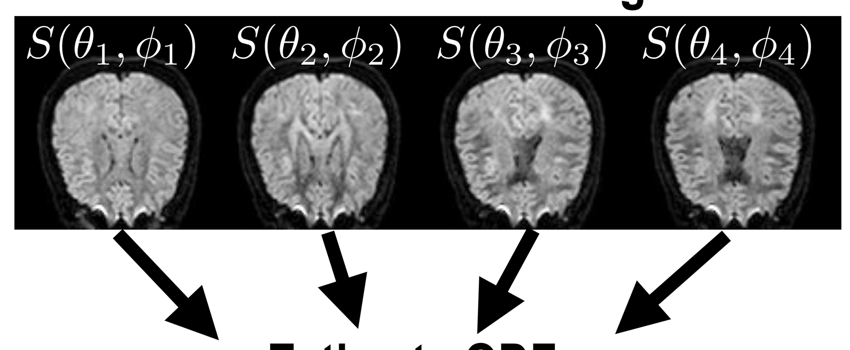
Contributions

In this work, we propose a general method to extract a large family of rotation invariant scalar features from any spherical function written in a spherical harmonic (SH) basis.

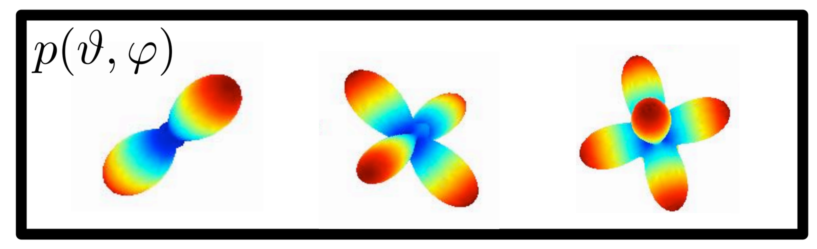
We extract physically meaningful features from the orientation distribution function (ODF), which describe and quantify its overall shape and distribution.

Feature Extraction Method

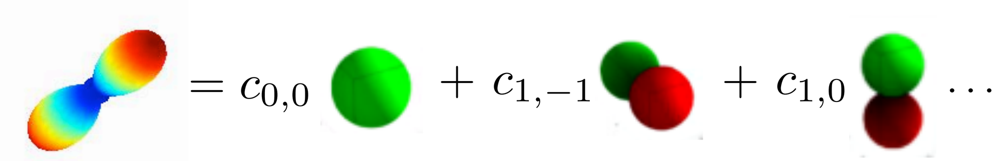
1. **Reconstruct HARDI Signal**



2. **Estimate ODFs**



3. **Represent ODF in terms of SH basis**



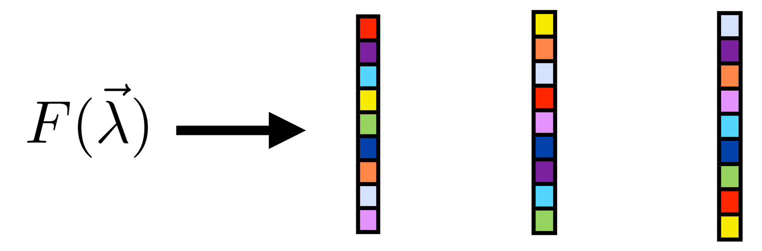
4. **Build matrix $T_L(p)$ from SH coefficients c_{lm}**

$$T_L(p) = \sum_{l=0}^{L} \sum_{m=-l}^{m=l} c_{lm} G_{lm}$$

5. **Calculate eigenvalues of $T_L(p)$**

$$\lambda_1^{(L)} \leq \lambda_2^{(L)} \leq \cdots \leq \lambda_{(L+1)^2}^{(L)}$$

6. **Extract rotation invariant features by forming any continuous function F of the eigenvalues**



Rotation Invariant Features

Rotation Invariance: The eigenvalues of $T_L(p)$ capture the distribution of the values of p, which does not change when we rotate the ODF. Therefore, any function of the eigenvalues gives a rotation invariant feature of the ODF.

Features		ODF
Min/Max Eigenvalue Variance/Range of Eigenvalues	⟷	Min/Max of ODF Variability/Shape of ODF
Low variance, range, max High variance, range, max Zero variance, range	⟷	Multi-fiber ODF Single-fiber ODF Isotropic ODF

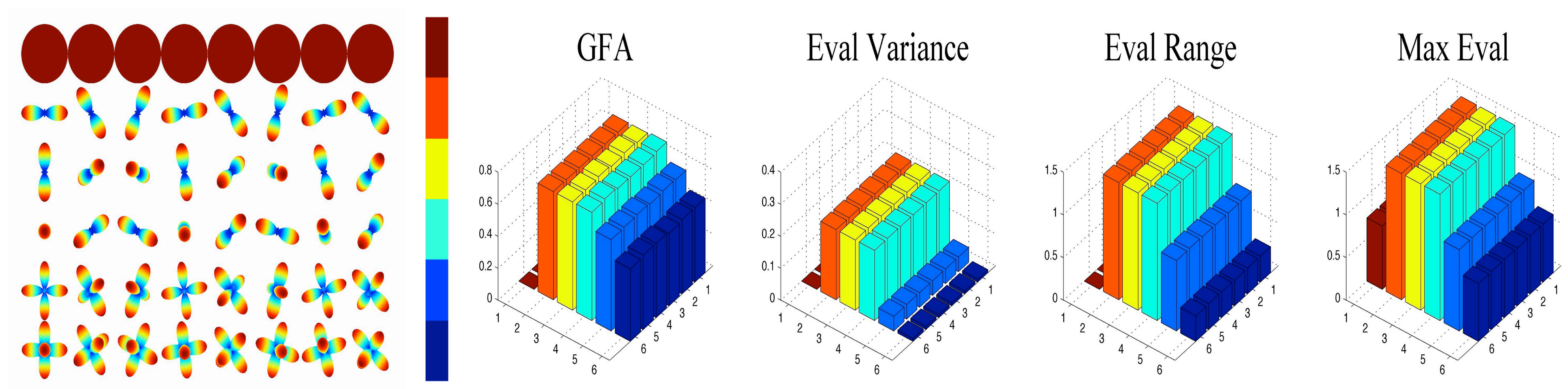
Experiments

Phantom Data: The eigenvalue variance of the ODFs is able to better segment fiber crossing regions than GFA, since the variance of a multi-fiber ODF is greater than a single fiber ODF.

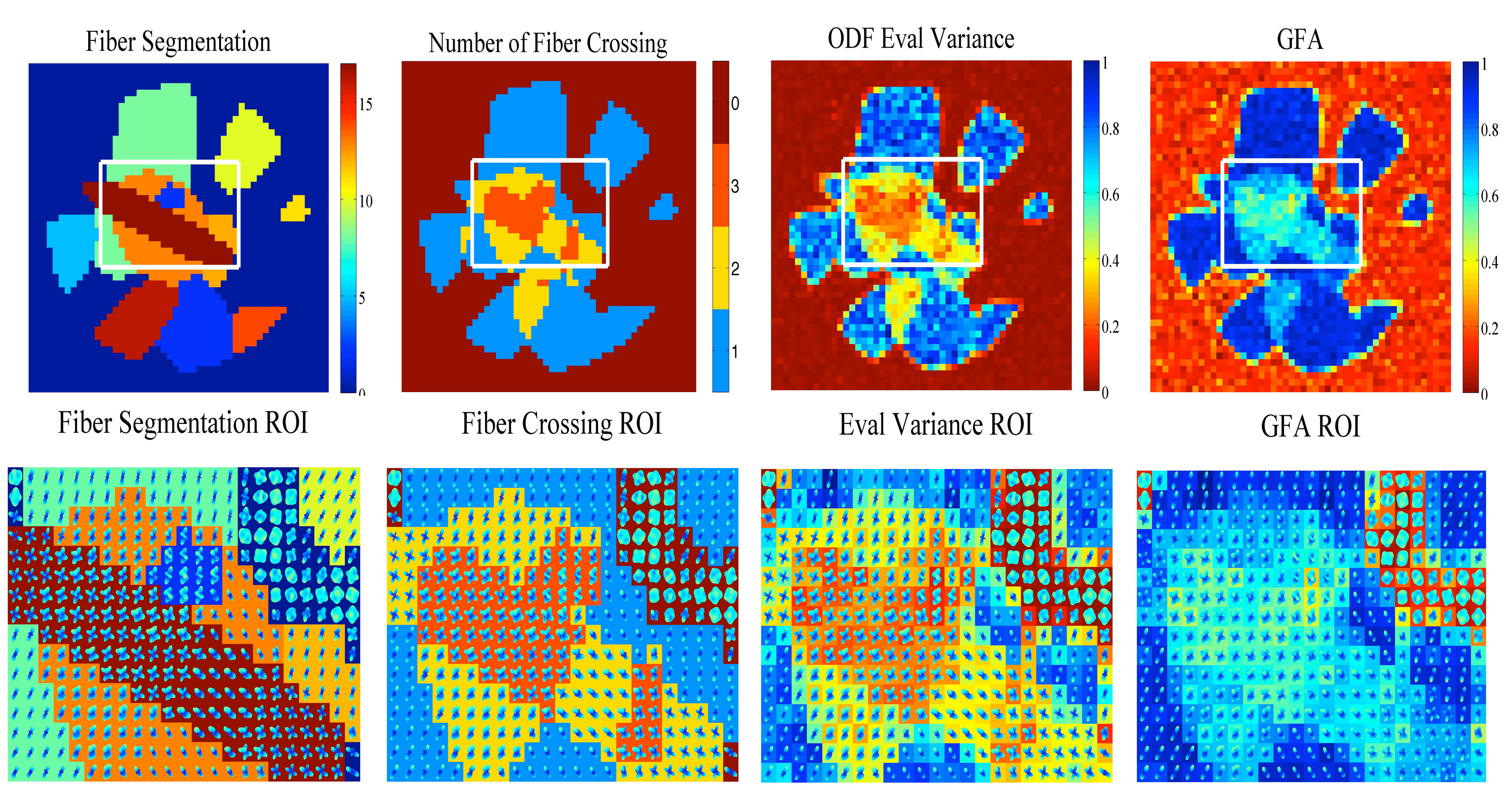
Real Data: The expected structure of the Optic Chasm (OC) is more visible with the smallest eigenvalue feature map than with the GFA.

Our generalized feature extraction method is capable of producing a large number of physically meaningful features for any spherical function relevant to dMRI with numerous applications in areas such as fiber segmentation, registration, and disease classification.

Synthetic Validation



ISBI 2013 Phantom Feature Maps



Real HARDI Brain Feature Maps