### **Optimizing the Metric for Brain White Matter Comparisons**

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# Introduction

Diffusion MRI is one of the most popular tools currently available to compare brain white matter structure between groups of subjects. In particular, in high angular resolution diffusion imaging (HARDI), scanning is performed using a large number diffusion sensitizing gradients directions, allowing modern image processing methods to resolve multiple fibers per voxels. In structural and diffusion tensor MRI, it has now become common practice when comparing two groups to make voxel-wise maps of the differences in a measure at each voxel, the fractional anisotropy, for example. A few recent studies have designed voxel-wise comparison methods for HARDI data. In particular, in [1], we advocated the use of a multivariate measure for HARDI group comparisons. Here we extend the above work by comparing statistical power for two scalar and two multivariate measures derived from the HARDI signal, as defined below.

#### Methods

Our data consists of 25 pairs of healthy young adult monozygotic twins (MZ; 10 men/15 women) and 25 same-sex pairs of dizygotic twins (MZ; 10 men/15 women) and (M 9 men/16 women). We acquired 11 baseline (b<sub>0</sub>) images and 94 diffusion-weighted images (b-value 1159 s/mm<sup>2</sup>) on a 4T scanner. The T1-weighted images of each subject were nonlinearly registered to a common template and the resulting deformation fields were applied to each of the gradient images to warp them to a common space.

We decomposed the ODF and the diffusion data into the modified spherical harmonic basis defined in [2]:

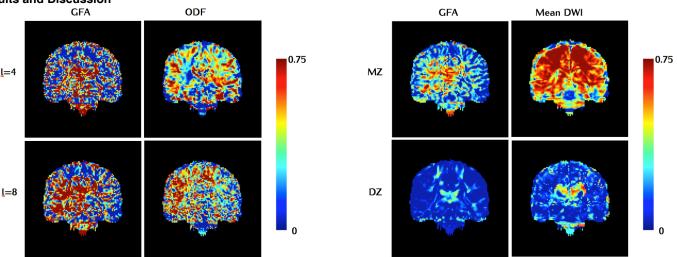
$$Y_i=\sqrt{2}Re(Y_l^{[m]})$$
 if  $m$ <0,  $Y_l^m$  if  $m$ =0, and  $\sqrt{2}(-1)^{m+1}Im(Y_l^m)$  if  $m$ >0 with  $l$  = 0, 2, 4, 6, 8, ... and  $m$  = - $l$ ,...,0,... $l$ 

(so I=0 for  $Y_1$  I=2 for  $Y_2,...,6$  I=4 for  $Y_7,...,15$  etc,...) We computed the intraclass correlation (univariate or multivariate, see [3]) on 4 measures: (1) the GFA, (2) the mean DWI, (3) the coefficients of the orientation distribution functions (ODFs, see e.g. [2]), and (4) the coefficients of the raw data. We compare the results of truncating the series at I=2,4 and 8. We compute the multivariate statistics on

 $|c_1|, \sqrt{|c_2|^2 + \ldots + |c_6|^2}, \sqrt{|c_7|^2 + \ldots + |c_{15}|^2}, \ldots$ 

where the decomposition is performed on the ODF (case 3) or the raw diffusion signal (case 4).

## **Results and Discussion**



A. Heritability computed for two level of truncation (I=4 and I=8) (see method) comparison between the univariate (GFA - left) and the multivariate (ODF right) measures

B- Intraclass correlation computed in the MZ and the DZ groups. Comparison between two univariate measures: the GFA (left) and the mean DWI signal

Fig. 1 show the heritability  $h^2 = 2*(ICC_{MZ} - ICC_{DZ})$  for the GFA (and the spherical harmonic decomposition of the ODFs. Results for the multivariate measure on the raw data were similar to those on the ODF and are not shown here. The top row shows  $h^2$  for l=4, and the bottom one for I=8. Heritability is detected at a larger number of voxels for the GFA with the addition of basis coefficients, while the added coefficients make the multivariate measures noisier. Results are consistent for both measures, but while they are confined to subcortical areas for the GFA, widespread heritability is seen throughout both subcortical and cortical regions with the multivariate measures. Fig. 2 shows the intraclass correlation for the two univariate measures. Correlations are higher in the MZs, as expected. The mean DWI shows higher and more widespread heritability.

In general, the signal sensitivity is expected to increase with multivariate measures. However, for a given study, the choice of measure will depend on the size of the dataset and the noise in different channels.

# References

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