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## Measuring Regional Diffusivity Dependency via Mutual Information

Xiang-zhen Kong, Zonglei Zhen, and Jia Liu

Abstract—We proposed an improved approach to measuring regional diffusivity dependency with diffusion MRI. Unlike the original approach, the improved metric can detect all types of regional dependencies. Systematical comparison was done.

#### I. INTRODUCTION

Diffusion Magnetic Resonance Imaging (dMRI) has been widely employed in brain research. Besides tractography, dMRI has also been extensively applied to depict regional microstructure of white matter (WM). A latest study [1] proposed a novel model-free metric (i.e., LDH, local diffusion homogeneity), defining as the regional inter-voxel coherence of diffusion series. However, quantified via Kendell's coefficient concordance (KCC), the metric can only detect monotonic relations. In fact, the actual diffusivity dependency is much more complex. In this study, we extended the inter-voxel metric by quantifying the regional diffusivity dependency (RDD) via mutual information (MI), which is more general and takes into account all types of dependency. To investigate its usability and distinguishing features, systematically analyses were conducted.

### II. METHODS AND RESULTS

The dMRI dataset (137 directions, 20 subjects,  $34.3 \pm 14.0$  years) was from the NKI-RS Multiband Imaging Test-Retest Pilot Dataset. After estimation of the diffusivity strengths along each gradient direction, we calculated the regional inter-voxel metrics within the neighbors (n = 27). In our improved approach (RDD), the MILCA estimator [2] was used, which is a robust MI estimator. At the same time, the KCC approach was used to obtain the LDH map. To compare between subjects, the maps were then projected onto the WM skeleton mask using the TBSS framework [3]. The RDD and LDH metrics both showed relative high test-retest reliability (RDD: Mean = 0.738; LDH: Mean = 0.746; with Intra-class correlation coefficient).

To evaluate the similarities and differences between the two metrics, we calculated spatial correlation and the

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across-subject correlation (with data from the first run). Fig. 1a shows two sample scatter plots of the across-space correlation (Mean r=0.897). Fig. 1b shows the non-significant voxels (3712) in across-subject correlation, which mainly located in the bilateral cingulum and superior longitudinal fasciculus. These results indicated that the two metrics were similar, but not exactly the same.

To further demonstrate the distinguishing features, a statistical analysis was performed using a general linear model (GLM), for the two metrics respectively, with gender as a confounding covariate, and age as the variable of interest. The results showed that elderly individuals exhibited significant decreased regional dependency in multiple regions such as bilateral anterior corona radiate and forceps minor (Fig. 1c). Though these reductions located in similarly for the two metrics, RDD successfully detected more age-related changes (RDD: 4245; LDH: 1802; Overlap: 1694; in voxel).

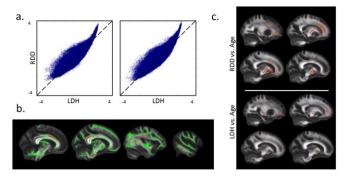


Figure 1. Distinguishing features between the RDD and LDH metrics. (a), Two sample scatter plots of spatial correlation between RDD (zscore) and LDH (zscore). (b), Non-significant voxels in the across-subject correlation (p > 0.01 after FDR correction). (c), The significant age-related WM changes revealed by the RDD and LDH metrics (p < 0.01, TFCE corrected).

All the results above suggested that the RDD metric could detect the individual differences in WM more sensitively and act as an important marker about WM microstructure.

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