Spatial Transformations of Fiber Orientation Fields

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Introduction:
It has been shown [1] that one third of voxels in a brain volume include more than one orientation of fibre bundles. To better consider this condition, recently, HARDI methods such as q-ball, DSI, PASMRI, Spherical Deconvolution methods [2, 3, 4, 5, 6], have been proposed. These solutions have demonstrated to be more accurate to describe white matter in regions with complex tissue organization and they have been included in some tractographic methods to overcome Diffusion Tensor limitations. To perform group-level analyses and compare subjects, due to differences in brain shape and size, geometrical transformations must be applied to images to overlap regions and compare signals or indexes. For DTI, the directional information can be considered using the (Preserve Principal Directions) PPD method proposed in [7]. For complex structures and HARDI techniques, Hong et al [8] have developed a method where the Jacobian of transformation is applied to each of the Fiber Orientation Distribution (FOD) directions. However, as Hong pointed out, FODs result to be deformed so that a compensation of direction length need to be done.

In this work we present a novel method that we call Preservation of Principal Branches (PPB), for the transformation of Fiber Orientation Distribution objects that takes into account the particularities of their shapes.

Methods:
FODs used in this work have been obtained from Lucy-Richardson spherical deconvolution technique [6]. In the case of an affine transformation, the PPB technique can be summarised as follows: 1) Classify the FOD shape into branches (each branch is a set of spatial directions that represents a single fiber bundle), see fig1c and 1d; 2) Compute the unit vectors $e_1$ and $e_2$, specific for each branch that characterize its orientation; 3) Compute the set of rotation matrices $\{R_j\}$ of the FOD accordingly with the transformation; 4) For each spatial direction on the final grid $\nu_i$, find the original direction, $R_j^T \cdot \nu_i$, according to each branch, and, consequently, calculate the value imposed by each branch, $\text{Branch}_j(R_j^T \cdot \nu_i)$, 5) The transformed FOD in the i-th spatial direction of final grid is then: $\text{FOD}(\nu_i) = \max_j(\text{Branch}_j(R_j^T \cdot \nu_i))$. In the case of higher order transformations, a local affine model $F_x$ can be obtained, for each image point x, as described in [5], and the appropriate reorientation matrices for each branch can be computed following the same PPB method.

Results:
In fig.2 the results of an affine transformation are shown. In particular, fig2a the original FOD before transformation, in Fig2b the results after the application of the simple Jacobian matrix, in Fig2c the results after Jacobian application and compensation of the lengths (similar to [8]). In Fig.2d the results after the application of the PPB method presented in this work.

Conclusion and Discussion:
In this work we have presented a novel shape-oriented method for transforming FODs. Other techniques do not take into account the FOD configuration characteristics after deconvolution. The important features of the FODs (principal branches) first have to be extracted and then transformations have to be applied to these elements. Preliminary results suggest that these transformations might be used for registration and normalisations of FODs and that may be applied to invocation data for comparison of subjects and group analyses.

References