Fiber Bundle Segmentation Using Major Diffusion Orientations in Reduced Position Orientation Space

E. Davoodi-Bojd[1], M. Nazem-Zadeh[2], H. Soltanian-Zadeh[1], and Q. Jiang[2]

[1]Control and Intelligent Processing Center of Excellence, School of Electrical and Computer Engineering, University of Tehran, Tehran, Iran, [2]Neurology, Henry Ford Hospital, Detroit, MI, United States

Introduction. High Angular Resolution Diffusion Imaging (HARDI) is a new imaging protocol can be used to obtain the Orientation Distribution Function (ODF). The ODF demonstrates the diffusivity behavior in each voxel and is calculated from typically more than fifty measurements each corresponds to one gradient direction. In [1], Hagmann et al proposed a method for revealing fiber bundle tracts by defining a five dimensional Position Orientation Space (POS). This space is composed of three dimensions for position and two dimensions for orientation information in each voxel. The POS can be very helpful in low resolution datasets. If two fiber tracts are irresolvable sharing crossing area in three dimensional space, they can be resolvable in five dimensional POS. Since four distinct peaks of the ODF data are in general adequate for describing diffusivity profile and extracting the fibers, we propose an approach in which using a novel strategy, the major directions from the ODF are computed, then they are employed for segmenting fiber bundles by an algorithm similar to that of Hagmann et al. This approach has two important advantages. First, the computational complexity of the problem is significantly reduced. Second, since the unknown parameters (labels of the sites) are decreased, the MRF algorithm converged more quickly. The results of our proposed method are superior than the results of Hagmann et al method.

Methods.

Artificial Data. The artificial pattern consists of one circle and two crossing line as shown in Fig. 3. The corresponding diffusion signals for each region were generated in 55 directions, similar to GE common Q-Ball protocol. For better evaluating the methods, we also added white Gaussian noise to the artificial diffusion signal to evaluate the effect of different noise levels. The ODF was then computed for each voxel in 755 points distributed on the unite sphere using the method of [2].

Reduced Position Orientation Space (RPOS). For extracting the major orientations of an ODF distribution (for example see Fig. 2) the proposed algorithm shown in Fig. 1 was used. The resulting major orientations are replaced in the Markov Random Field (MRF) (the method of [1]) instead of the whole ODF data. Therefore, in our method named Reduced POS (RPOS), maximum four sites are located on the unit hemisphere pointed to the major diffusion orientations of each voxel. Using this approach, the POS of ODF data is reduced considerably to the RPOS in which the orientation information is preserved as well. Therefore, the calculation complexity of the problem is decreased by a significant factor (for our case 755/4≈188) which means that it is considerably faster than the POS based method.

1. The ODF signal is normalized so that its values are set between 0 and 1.
2. The principal orientation with the maximum ODF scalar (which is equal to 1) is found and the other orientations are sorted based on the angular distance from this orientation. The resulting profile of this arrangement demonstrates the number of major diffusion orientation, as shown in Fig. 2(b).
3. Due to the symmetry of the profile, only the first half of the points is considered. In addition, the ODF values smaller than a threshold of 0.1 are eliminated.
4. Using a derivative based maximum detection algorithm, the maximum points of the signal are calculated.
5. The step 4 is repeated until we have maximally a number of maximum points. This number should be in a proper range to have sufficient number of candidates of peaks for the next step. We set this number to 12.
6. The resulting peaks are clustered into maximum 4 groups based on the distance of their spatial positions. The linkage clustering algorithm can be used in this step.
7. For each cluster its maximum ODF value is found. This value and its corresponding direction are stored as a final detected major orientation for that voxel. The resulting major orientations are shown in Fig. 2(c).

Fig. 1. The proposed algorithm for extracting the major orientations

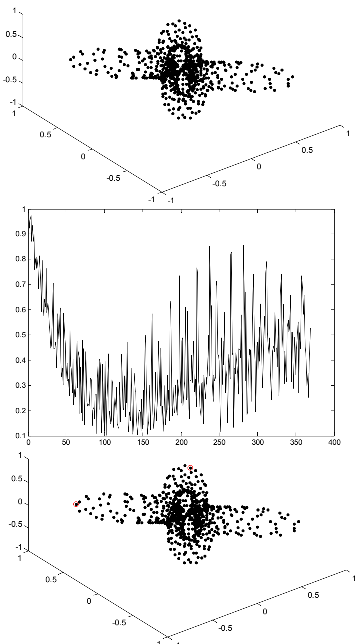

Fig. 2. Progression of the algorithm on an ODF sample.

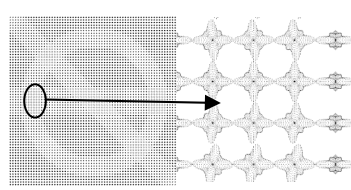

Fig. 3. Artificial pattern.

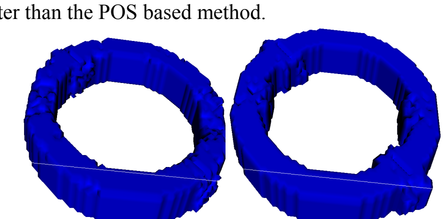

Fig. 4. The segmentation results of RPOS (left) and POS (right) methods, SNR=20

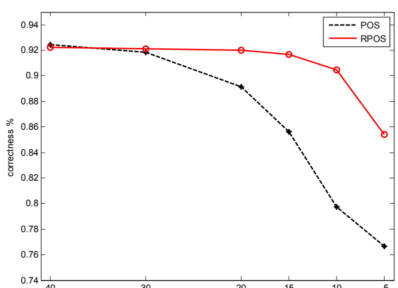

Fig. 5. Comparison of the methods over different SNR values.

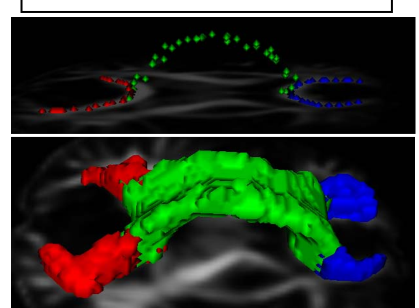

Fig. 6. The initial seed points (top) and the final results (bottom).

Results and discussion.

Artificial Data. The segmentation results of applying POS and the proposed RPOS methods for SNR of 20 are shown in Fig. 4. For better comparison, in Fig. 5, the correctness measures resulted from both methods are also shown. As this figure shows, in high SNR values the POS and the proposed RPOS methods work well. However, the RPOS method generates better results in low SNRs, which means that it is more robust to the noise (see Fig. 5). This can be interpreted by reminding that the RPOS method is based on the major diffusion orientations. On the other hand, the major orientations are macroscopic features of a voxel, therefore, they are more robust to the noise than the individual ODF directions which are used in the POS method.

Real Data. In order to apply the proposed method on the real HARDI data, a normal subject was scanned by a GE Signa Excite3T MRI system in Henry Ford Hospital (Detroit, MI) through a Q-ball Imaging protocol with 55 diffusion gradient directions and 6 B0 reference images with imaging voxel dimension of 0.975x0.975x2.6. For segmentation task, one must specifies multiple seed points from each fiber bundle which is performed by use of FEFA (fractional anisotropy weighted First eigenvector) map and comparing it with an atlas including major fiber bundles [3]. In this work, we selected three tracts: Corpus Callosum body, its Forceps Major and Forceps Minor fiber tracts. The initial selected points and the final segmented fibers are shown in Fig. 6. The results confirm the ability of the proposed RPOS method for segmenting fibers in real data.

References. [1] P Hagmann et al. NeuroImage, 32:665–675, 2006. [2] M Descoteaux et al. Magn. Reson. Med., 58:497-510, 2007. [3] S Wakana et al. Radiology, 230:77-87, 2004.