Effect of Spherical Harmonic Coefficients on Fiber Bundle Segmentation

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Abstract

Nowadays classifying the brain white matter fibers into the distinct object named as bundles inside which the same characteristics on local diffusivity or shape and length of fibers exist, is of a growing interest in neuro-imaging fields. In this paper we present a method for segmenting the fiber bundles using Spherical Harmonic Coefficients (SHC) which describe diffusion signal obtained from High Angular Resolution Diffusion Imaging (HARDI) protocols. Using SH coefficients in defining of a similarity measure being used in speed function term in Hamilton-Jacobi equation with Levelset framework as an implicit numerical solution, we have shown that our method has advantages over methods using similarity measures based on DTI field by proper propagating of the front within fiber crossing areas. Without any assumption about diffusion profile or model by dealing with just diffusion signals instead of diffusion probability function most used in other studies, out results on synthetic data as well as real HARD MRI data are surely closer to reality.

Keywords: Fiber bundle Segmentation - Spherical Harmonics Coefficients- Levelset- Diffusion MRI.

I. Introduction

Diffusion Magnetic Resonance Imaging is an approved non-invasive clinical tool to investigate white matter tissue structures within the brain by qualifying macroscopic effect of water molecules diffusion which is barred or hindered by these microscopic structures. Basser et al.[1,2] in 1994 assumed a three dimensional Gaussian profile for diffusion of water molecules and modeled its behavior by a symmetric positive semi-definite matrix i.e., tensor. As the tensor model can only describe Gaussian diffusion behavior which is valid for free diffusion or isotropic restricted diffusion in all directions or anisotropic diffusion of just one major white matter fiber population, it fails to model higher order anisotropies in heterogeneous areas where more than one fiber population exist.

For this reason some clinically feasible acquisition imaging schemes with great amount of diffusion synthesizer gradients were introduced and named as High Angular Resolution Diffusion Imaging i. e., HARDI. Moreover new model-based analysis such as Multi Tensor fitting[4] or Spherical Deconvolution [5,6], non-linear Spherical Deconvolution [7], or PASMRI[8] and some model-free analysis like q-ball[9] were proposed to analyze HARD data in order to obtain Orientation Distribution Function or ODF from which main diffusion directions can be extracted. However, using ODF instead of pure diffusion signal needs some simplifications and approximations which make ODF calculation be almost infeasible as a preprocessing step.

For visualizing of tensor or diffusion signal or profile within the brain white matter, some primitives were introduced, however reconstructing of virtual fiber paths within the brain is of more interest which presents virtual anatomical connectivity within the brain and gives better understanding of underlying diffusion profiles in voxels. For obtaining fiber paths, one can do individual fiber tracking or tractography and extract curvilinear trajectories in three-dimensional space in DTI or HARD data fields. Another alternative which is typically more robust than tractography, is segmenting of volumetric regions each contains similar local diffusivity characteristics or similar fibers in shape and length together as a distinct object named as fiber bundle. The task of classifying the brain white matter fibers can be performed in one of two methodologies: Clustering fibers resulted from tractography into the bundles[10, 11] or segmenting the bundle via front propagation based on local properties of diffusion tensor, signal or profile[12- 19]. Since clustering methods rely on tractography algorithm results, they shall not be properly validated if tractography step is

not performed well especially streamline types in critical situations like kissing, branching, merging and crossing status. However segmenting the bundle via front propagation is a more powerful tools especially in above mentioned status. Most of these studies concentrate on scalar quantities like anisotropy maps derived from tensor data regardless of complete tensor information [12], while some other studies try to benefit from the whole information contained in diffusion tensor[13- 16]. They typically extract some similarity measure between successive tensors and the insert these measures into a region based segmentation framework like levelset [17]. When segmenting white matter regions in DTI, the similarity measure emphasizes anisotropic regions. Since tensor model specifies a spherical or planar tensor shape to the multimodal diffusion profile in heterogeneous areas where more than one major fiber population exist, the similarity measure between neighboring tensors prevents the front from propagating from a voxel of one fiber population with prolate tensor shape into the next voxel of the same fiber orientation population crossed by other fiber population with spherical tensor shape obtained by tensor model.

In a different study by increasing problem dimension, A position-Orientation Space or POS has been introduced by combining Euclidian spatial domain with spherical ODF space from HARD data where two crossing fiber population in spatial domain with different orientations can be simply resolved by applying a front propagation method in Levelset framework in this 5 dimensional space. Although dimensional reinforcement of the problem causes some disadvantages like increasing of computational costs.

In [19], fiber bundle segmentation has been performed in POS based on Markovian Random Fields (MRF). Assuming some spatial relationship which can be modeled by MRF, the goal of this method is to estimate a hidden random field of fiber bundles from realization of observed ODF profiles with Maximum A Posteriori (MAP) formulization and Iterative Conditional Modes (ICM) implementation.

If we expand a spherical function by spherical harmonics bases, we will obtain SH coefficients which are descriptor features of that function on the sphere [20-23]. In this paper we present a method for segmenting the fiber bundles using SH coefficients which describe diffusion signal obtained from High Angular Resolution Diffusion Imaging (HARDI) protocols. Using SH coefficients in defining of a similarity measure being used in speed function term in Hamilton-Jacobi equation with Levelset framework as an implicit numerical solution, we have shown that our method has advantages over methods using similarity measures based on DTI field by proper propagating of the front within fiber crossing areas. Without any assumption about diffusion profile or model by dealing with just diffusion signals instead of ODF most used in other studies, out results on synthetic data as well as real HARD MRI data are surely closer to reality. By applying the proposed method on real HARD MRI data, we were capable to segment some major fiber bundles as Corpus Callosum and Corticospinal as well.

Having these distinct fiber bundles together, in addition to access to a white matter mask composed of them, one can avoid of propagating of fibers from some bundles to the others and the applied fiber tracking algorithm will be more robust against crossing, branching and merging situation between bundles, themselves. Moreover the results can be used as a regularizing term beside data term in fiber tracking algorithms. Besides, we can benefit from the smoothing property of SH representation of diffusion signal in order to reduce imaging noises as outliers induced in DWI Images.

II. Theory

The expansion of a function on a sphere using spherical harmonics is equivalent to the generalization of Fourier representation to the spherical coordinates, which can be used in many applications [20, 21]. By expanding the diffusion signals of HARD data using these basis harmonics and calculating the harmonic coefficients, it has been proposed a linear method for calculating ODF.

The spherical harmonics, which are represented by Y_l^m (l is order and m is phase factor), consist a basis for complex functions on the unit sphere, and they are defined by the fallowing relation.

$$Y_l^m(\theta,\phi)=\sqrt{\frac{2l+1}{4\pi}\frac{(l-m)!}{(l+m)!}}P_l^m(\cos\theta)e^{im\phi} \tag{1}$$

where $\theta\in[0,\pi],\phi\in[0,2\pi]$ and P_l^m is the associated Legendre polynomial. Having $l=0,2,4,...,l_{\max}$ and $m=-l,...,0,...,l$, it is assumed that $j=j(l,m)=(l^2+l+2)/2+m$, the modified basis is defined as fallows [21]:

$$Y_j=\begin{cases}\sqrt{2}((-1)^m Y_l^m+Y_l^{-m})/2, & if\ -l\le m<0\\ Y_l^0, & if\ m=0\\ \sqrt{2}i((-1)^{m+1}Y_l^m+Y_l^{-m})/2, & if\ 0<m\le l\end{cases} \tag{2}$$

Therefore, the diffusion signal can be estimated on any point of the unit sphere using the spherical harmonic coefficients by the following equation.

$$S(\theta_i,\phi_i)=\sum_{j=1}^{N}c_jY_j(\theta_i,\phi_i) \tag{3}$$

in which c_j is the j[th] spherical harmonic coefficients and $N=(l+1)(l+2)/2$ is the total number of these coefficients. The mathematical relations for calculating these coefficients are given by [21]. The 8[th] order spherical harmonic coefficients in each voxel can represent diffusion profiles with maximum 4 major distinct peaks. Therefore, they can be used directly as features to separate voxels with dissimilar diffusion signals, and to merge voxels with similar diffusion signals. The similarity measure function for comparing two diffusion signals *S* and *S'*, based on the spherical harmonics, has been defined as fallows [21]:

$$< S, S' >= \int_{S^2} S(q).S'(q)dq = \int_{S^2}\left(\sum_{i=1}^{R} c_i Y_i(q)\sum_{j=1}^{R} c'_j Y_j(q)\right)dq \qquad (4)$$
$$< S, S' >= \sum_{i=1}^{R} c_i c'_i$$

where c_i and $c_i^{'}$ are the spherical harmonics for signals *S* and *S'* ,respectively.

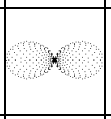
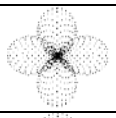
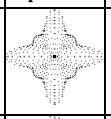
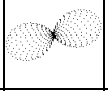
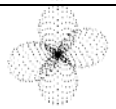
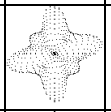
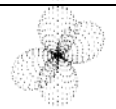
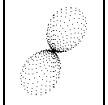
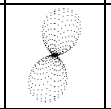
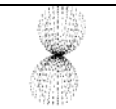
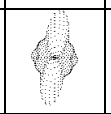
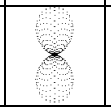
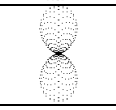
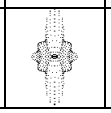
As we discussed above, the spherical harmonics can be used as features for comparison between diffusion signals. On the other hand, in segmentation methods based on levelset algorithm, it is necessary to define a criterion for evolving levelset function. Therefore, in the proposed method, by computing spherical harmonic coefficients from HARDI data, the similarity measure is calculated between neighboring voxels using (4) in order to build the speed function of levelset algorithm. Then, this procedure is used to segment white matter fiber bundles.

III. Methods

a) Investigating of SH Characteristics by Simulation

In order to investigate the effect of SH coefficients in comparing diffusion signals, an artificial uni-polar diffusion signal is rotated between 0 and 90 degree in 15 degree steps. This rotation is also done on one pole of an artificial bi-polar diffusion signal. Then, the 8[th] order SH coefficients of each signal is computed. Assuming a reference voxel with one major diffusion orientation, (see Table. 1), the simulation results show that the similarity measure between SH coefficients of the reference voxel and SH coefficients of the other voxel with a major diffusion orientation and a determined angular difference, is quite equal to the similarity measure between SH coefficients of that reference voxel and SH coefficients of another voxel which has another major diffusion orientation in addition of that major orientation. Therefore, the front can evolve into that voxel, properly.

Table 1 Spherical illustration of artificial linear and planar diffusion signals using spherical harmonics. The similarity with reference signal for each signal is also shown.

Deg.	Uni-modal Diffusion Signal	Similarity with reference signal	Bi-modal Diffusion Signal		Similarity with reference signal
			Multi tensor	Signal profile	
0		1.000			0.956
15		0.7620			0.7616
30		0.3621			0.3543
45		0.1508			0.1470
60		0.0659			0.0628
75		0.0250			0.0246
90		0.0195			0.0195

b) Implementation of the Proposed Method on Artificial Data

In order to determine the capability of the proposed method in segmenting of fiber bundles, an artificial pattern of diffusion signals which consists of two crossing bundles was created as illustrated in Fig. 1. As it can be seen in the crossing region the diffusion signals have two major diffusion orientations which can be a good criterion for determining the capability of the method. For comparison, instead of (4), a common similarity measure for tensors is also used in levelset algorithm, which is defined as [17]:

$$< D_1, D_2 >= \frac{trace(D_1.D_2)}{trace(D_1).trace(D_2)} \qquad (5)$$

Finally, by implementing the levelset algorithm using two similarity measures (equations (4) and (7)), the results show that using SH coefficients the segmentation results are enhanced. To quantify the results, the correctness of segmentation results is calculated using the fallowing relation:

$$correctness = \frac{N(S_o \cap S_r) - N(\overline{S_o} \cap S_r)}{N(S_o)} \qquad (6)$$

In which the S_o and S_r are the target and resulted structures, respectively, and *N* is the number of voxels laying in each structure. In the Table 2 the correctness measure for each method is shown.

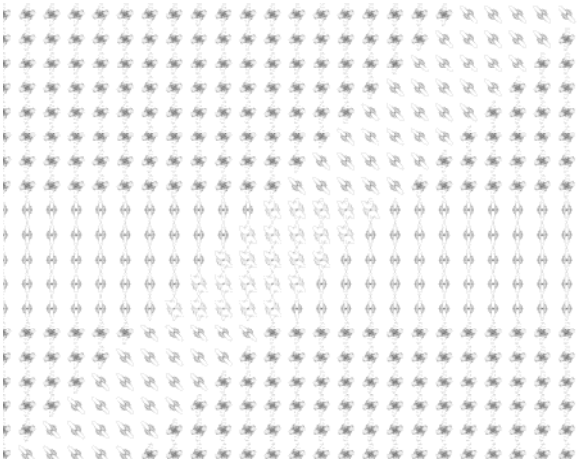


Fig. 1 Illustration of the artificial crossing pattern for diffusion signals with 8th SH.

c) Implementation of the Proposed Method on Real Data

In order to apply the proposed method on real HARD MRI data, a normal subject was scanned by a GE Signa Excite1.5T MRI system (General Electric medical systems, Milwaunkee, WI, USA) in Stanford Lucas Imaging center through a Q-ball Imaging protocol with 492 diffusion synthesizer gradient scheme and 13 B0 reference images with imaging volume dimension equals to 128x128x33 and imaging voxel dimension equals to 1.95x1.95x4.5.

After some preprocessing like applying a Gaussian kernel on data, registering diffusion on a reference volume and reordering diffusion signals from scanner-wise to voxel-wise order, we calculate SH coefficients with order of 8 to every voxel diffusion signal pro the equation introduced in section 1-2. For segmentation task, one must specifies a seed point from each fiber bundle which is performed by use of FA(Fractional Anisotropy) map and comparing it with an atlas including major fiber bundles. As mentioned in section 2.2, by calculating the similarity measure between neighboring SH coefficients, the speed function in levelset framework is obtained. However it is not mandatory to calculate the speed function in all of imaging volume voxels, since the front propagation in every step time depends on only the speed function on boundary points. Moreover in order to prevent from computational errors, this function must be specified in a wide-enough stripe with 5 points around the boundary [25].

In Fig 2, the suggested segmentation algorithm results for two major fiber bundles i.e. Corpus Callosum and Corticospinal Tract have been demonstrated where the algorithm is able to isolate these two fibers from HARD data field. Due to a better comparison, the result of segmentation of Corpus Callosum for two similarity measure extracted from SH coefficients and tensor are shown with the fiber obtained by streamline tractography as a common fiber tracking algorithm [26] in Fig. 3. As illustrated, the result of our SH coefficients segmentation method is more proper than segmentation based on tensor similarity measure.

IV. Conclusions

In this paper we presented a method for segmenting the fiber bundles using Spherical Harmonic Coefficients with order of 8 which describe diffusion signal obtained from High Angular Resolution Diffusion Imaging protocols, as well. We utilized SH coefficients in defining of a similarity measure being used in speed function term in Hamilton-Jacobi equation with Levelset framework. We have shown that our method has advantages over methods using similarity measures based on DTI field by proper propagating of the front within fiber crossing areas without any assumption about diffusion profile or model by dealing with just diffusion signals. We demonstrated the results of segmentation for Corpus Callosum and Corticospinal Tracts as two major fiber bundles inside brain white matter. We plan to use SH coefficients as a powerful feature descriptor within other segmentation frameworks rather than levelset.

Table 2 results of segmentation correctness for each method.

Progress time	t=0.2	T=0.4	t=0.6	t=0.8	T=1
Tensor	0.092	0.412	0.534	0.782	0.928
S.H.	0.141	0.336	0.519	0.597	0.658

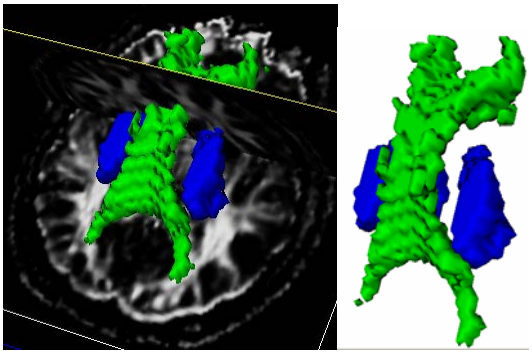
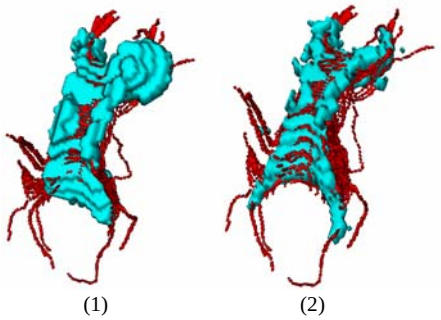


Fig. 2 results of suggested SH coefficients segmentation algorithm for Corpus Callosum and Corticospinal Tracts



(1) (2)

Fig.3 Comparison between results of suggested SH coefficients segmentation algorithm (1) and traditional tensor segmentation algorithm (2) (in blue) plus streamline tractography (in red) for Corpus Callosum

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