Fiber feature map based landmark initialization for deformable DTI registration

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Abstract. The abstract should summarize the contents of the paper using at least 70 and at most 150 words. It will be set in 9-point font size and be inset 1.0 cm from the right and left margins. There will be two blank lines before and after the Abstract. ...

Keywords: computational geometry, graph theory, Hamilton cycles

1 Method

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1.1 Feature Map Generation

In this section, we present the steps involved in generating the feature map from the raw diffusion weighted image (DWI) and the image mask. First, we perform a 2-tensor unscented kalman filter based tractography [1] inorder to obtain the fiber tracts image. Once the fiber tracts have been generated, we compute two main features namely, number of fiber segments per voxel and entropy of fiber orientations per voxel. We normalize and combine these two features inorder to develop the feature image. The following sections describe each step of the feature map generation in detail.

Fiber Tracts Generation The fiber tracts are generated from the raw DWI image and the image mask by performing a 2-tensor unscented kalman filter (ukf) based tractography. Unlike many of the existing techniques, in ukf-based tractography, fiber tracking is formulated as causal estimation; at each step of tracing the fiber, the current estimate of the signal is guided by the previous. To do this, the signal is modeled as a discrete mixture of Watson directional functions and tractography is performed within a filtering framework. Starting from a seed point, each fiber is traced to its termination using an unscented Kalman filter to simultaneously fit the signal and propagate in the most consistent direction. Despite the presence of noise and uncertainty, this provides an accurate estimate of the local structure at each point along the fiber. The in-depth details of the tractography can be found in [1]. While generating the fiber tracts for our experiments, we configured the number of seeds per voxel as 8, seed FA limit as 0.18, minimum FA to continue tractography as 0.12 and branching was suppressed while using multiple tensors.

Fiber Segments per voxel In this step, we traverse through all the fiber segments in the fiber tracts generated and identify which voxel a particular fiber segment belongs to and increment its counter by one. The result of this step is an image where the value at a particular voxel indicates the number of fiber segments it contains and thus indicates the density of fibers at that voxel.

Entropy of Fiber Orientations In order to compute the entropy of fiber orientations at a particular voxel, we first need to define what is the fiber orientation at a voxel. Consider the below example in Figure 1, where a single fiber passes through the fiber points p1, p2 and p3 at a particular voxel. The fiber orientation at a fiber point is defined as the direction of the tangent joining its neighboring fiber segment points. At the boundary fiber points, the fiber orientation is defined as the direction of the line connecting it to the previous or subsequent fiber point. The fiber orientation at a voxel can now be defined as a tuple of fiber orientations at the fiber points contained in the voxel.

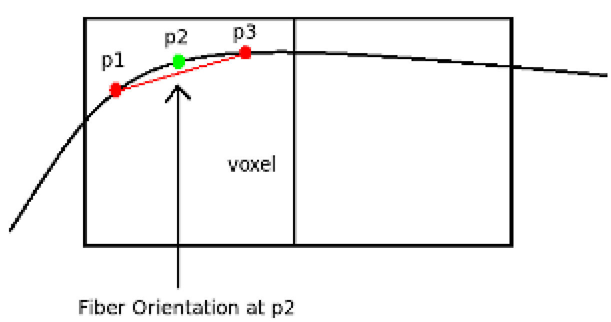

Fig. 1. The figure depicts the fiber orientation computed at fiber segment point p2 i.e., the tangential direction connecting its neighboring fiber segment points p1 and p3.

The next step is to compute the histogram (see Figure 2) of these fiber orientations at each voxel. This histogram computed is on a unit sphere which is subdivided into equal regions by fitting a platonic solid such as an icosahedron onto the surface of the sphere with a sub-division level of 6. At the subdivision level of 6, we get 492 icosahedron vertices and given a fiber orientation, we approximate it to a particular icosahedron triangular face and add it to the icosahedron vertices using barycentric coordinate system in which the location of the fiber direction is specified as the center of mass, or barycenter, of masses placed at the vertices of a simplex i.e., a triangle in our case.

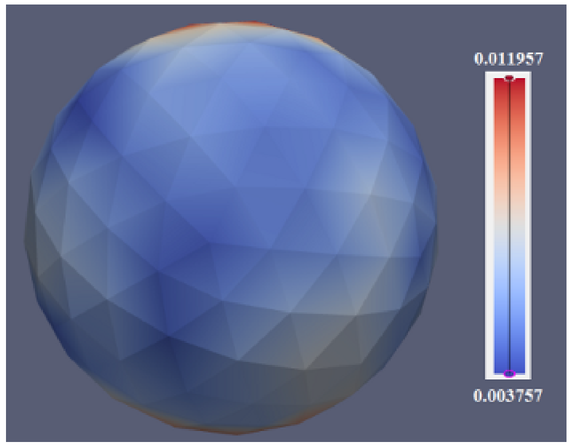

Fig. 2. The figure shows the histogram representing the fiber orientations of a particular voxel on a unit sphere which is subdivided into equal regions by fitting a icosahedron onto the surface of the sphere.

This histogram is then used to generate the entropy of fiber orientations. Entropy is a measure of disorder, or more precisely unpredictability. For example, a series of coin tosses with a fair coin has maximum entropy, since there is no way to predict what will come next. A string of coin tosses with a coin with two heads and no tails has zero entropy, since the coin will always come up heads. Similarly if there is just a single track fiber, there is less unpredictability and hence lower entropy and if there are multiple fiber tracts and multiple fiber orientations, this means that there is more unpredictability and hence higher entropy.

Using the histogram, we compute entropy of fiber orientations per voxel as below:

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log_b p(x_i) \tag{1}$$

where, $H(X)$ is the entropy of fiber orientation at a particular voxel, $p(x_i)$ is the probability of a fiber orientation to be x_i and n represents all possible fiber orientations.

Combining features to obtain Feature Map In order to obtain the feature map, we first normalize the two features namely fiber segments per voxel and entropy of fiber orientations per voxel by dividing each of these by their respective maximum. The feature map is then obtained by computing the square root of the product of normalized values of the two features.

$$F_i(X) = \sqrt{\frac{H_i(X)}{maxH(X)} * \frac{fs_i(X)}{maxfs(X)}} \tag{2}$$

where $F_i(X)$, $H_i(X)$ and $fs_i(X)$ are the feature map value, entropy of fiber orientations and the number of fiber segments at voxel i respectively, $max\ H(X)$ and $max\ fs(X)$ are the maximum values of entropy of fiber orientations and number of fiber segments over the entire image.

This feature map is certain to highlight the crossing fiber landmarks which can further be used for DTI registration. If one examines the fiber segments per voxel image, it is bound to have higher intensities in those regions where there are large number of single fiber tracts and multiple fiber tracts and lower intensities in regions of fewer or no fiber tracts. The entropy of fiber orientations image has higher intensities in regions of dispersed single fiber tracts and crossing fiber tracts (due to greater variation in fiber orientations) and lower intensities in uni-directional single fiber tracts or no fiber tracts regions. Hence, by combining these two, we can negate out the uni-directional single fiber tracts and no fiber tracts regions, thus highlighting the crossing fiber regions or landmarks.

2 Results

2.1 Feature Images

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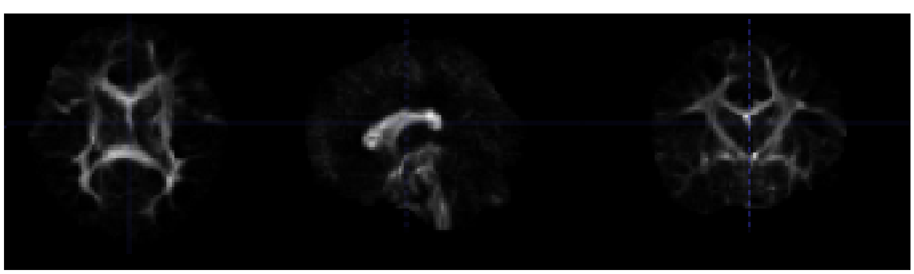

Fig. 3. Fiber Segments per voxel image

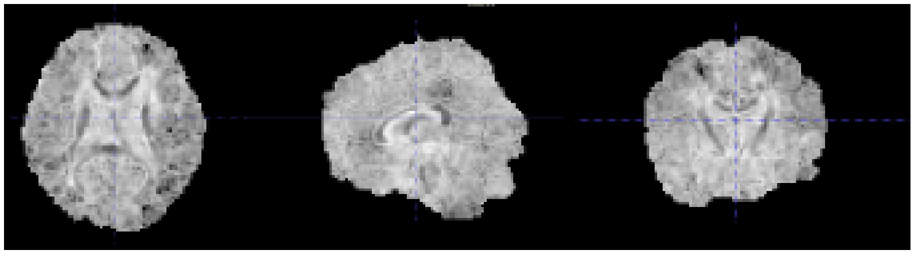

Fig. 4. Entropy of fiber orientations per voxel image

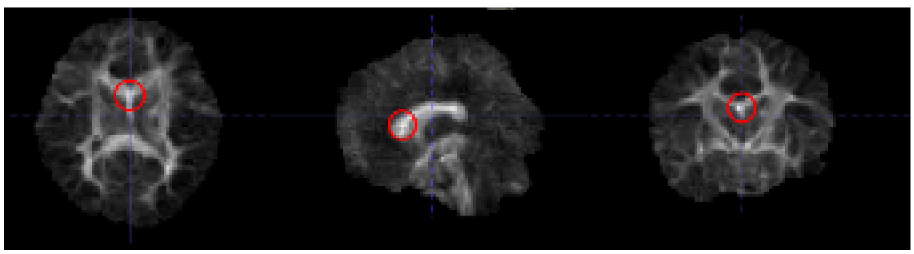

Fig. 5. This figure shows the combined feature map image. The crossing fiber landmarks which have higher intensities are also highlighted in this image

References

1. James G. Malcolm, Oleg Michailovich, Sylvain Bouix, Carl-Fredrik Westin, Martha E. Shenton, Yogesh Rathi: A ltered approach to neural tractography using the Watson directional function Med Image Anal. 2010 Feb;14(1):58-69 (2009)