A new approach for streamline based tractography registration

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Abstract. Registration of white matter tractography is a process to align different tractographies from different scanner spaces (or coordinate system) in one common space. Most commonly used tractography registration is Fractional Anisotrophy (FA) image registration mappings or affine transformation applied on tractography. Recent tractography registration is mostly focus on the streamline or fiber registration where no prior information rather then the tractography themselves is needed. Although there is no specific solution of the direct registration is available, it becomes an open problem to solve multi-subject whole brain tractography registration. Here, we have proposed a new and robust approach for streamline based registration with directly mapping the streamlines in native space.

Key words: Tractography, Registration, dMRI(Diffusion Magnetic Resonance Imaging)

1 Introduction

In neuroscience, dMRI (Diffusion Magnetic Resonance Imaging) is used for measuring the displacement distribution of water molecules and applied for the extraction of neuronal fibers [1, 2]. Tractography, reconstructed 3D path-ways of axons within the white matter of a brain extracted from dMRI as a set of streamlines, allows us to study anatomical connectivity of the brain. A full brain tractography is a large collection of streamlines, approximately the number of streamlines are $3 * 10^5$. Fig. 1 shows the collection of streamlines from a full brain. Nowadays in the field of neuro-imaging, tractography data reconstruction and analysis plays a vital role for both diagnosis and clinical applications.

Tractography is created in two steps: reconstruction and tracking. At Reconstruction level, the orientation of streamlines at every voxel has been obtained from the raw data. A single streamline has reconstructed from those information by tracking method. The main purpose of tractography is to clearly observed the orientation of tissues by integrating the pathways of maximum diffusion coherence. Both deterministic and probabilistic [3] algorithms are available for tractography reconstruction. Fig. 2 shows the procedure of deterministic tractrography reconstruction.

Theoretically, image registration [9] is a process to wrap or align images in a common space. Main goal of registration is to find a way to combine an image

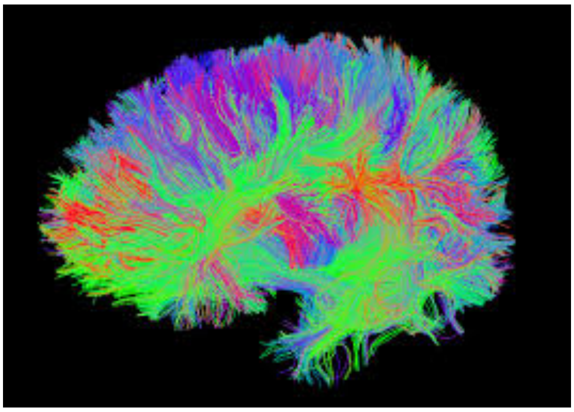

Fig. 1. Whole brain Tractography

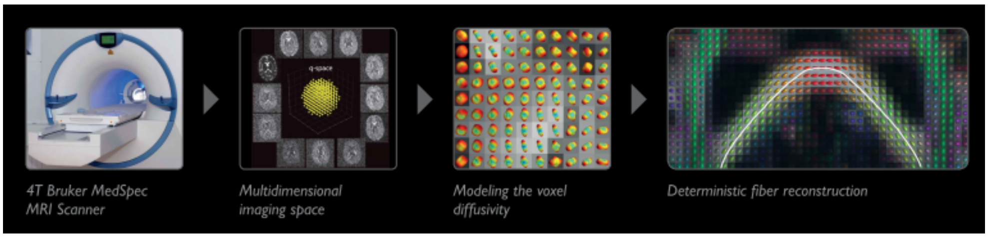

Fig. 2. Deterministic Tractography reconstruction

of the same subject with different modality to a reference image by geometric transformation. Rapid development of medical image acquisition devices and diversity of images make these registration techniques more essential for image analysis. In the last three decades, medical image registration has been investigated and surveys of recent and classic image registration techniques can be found in [4]-[8].

For diffusion tractography data analysis and segmentation or labeling different tracts, it is necessary to align tractography from different brains together or combine different tractographies of same brain for follow-up. As because, initially all the tractographies in the space of scanner with different coordinate, they need to wrap them together for further analysis using different image registration techniques.

Different authors classified tractography registration in different ways. Some classification are based on what kind of Diffusion data are used [10] and some are based on what kind of registration techniques are used [11]. And if we consider from the point of registration technique, it is basically based on different similarity measures: rigid, non-rigid registration; linear, non-linear registration and the feature based registration. According to the data type registration, there are three alternative approaches: scaler or vectorial registration, tensor registration and fiber or streamline registration. We choose to keep the registration based on data type to elaborate. It is important to mention that all the three term: *streamline, fiber and tract* have the same meaning. Afterward, we use the three terms interchangeably.

From scalar image based registration point of view, mutual information is used to measure the similarity between images. Affine co-registration along with mutual information is performed with diffusion weighted images [12]. Orientation information of the diffusion tensor preserves after affine transformation in order to align anatomical structure. Scalar registration are used at early stage of dMRI registration with the scaler images; without considering the directional images. Many other similar methods can be found in [13, 15].

As previously mentioned tensor based method, FA (Fractional Anisotrophy) mapping or affine registration is applied on tractography along with tensorial value of the images. We can distinguished tensor based registration with the scalar registration by additional deformation model which keep the tensor orientation consistent according to the anatomical structure of the image. Direct and feature based methods are discussed in [16], where direct approach is based on Diffusion Tensor Constancy Constraint (DTCC) along with finite strain reorientation schema. Feature based method is based on singular value decompositions (SVD).

Above described image based and tensor based model are voxel based registration and by considering the anatomical images, not on 3D reconstructed tractography. Traditionally structural dMRI images are wrapped to MNI space from native space. A transformation matrix collected from previous steps are used to align the different tractographies. In fiber or streamline registration, the concept is to register the tractography in native space directly. In few publications, fiber or streamline based method are proposed but there are no general and well accepted solution is available. Therefore, our main aim is to register the fiber or streamline without any prior knowledge of structural images and any kinds of transformation.

2 State of the art

As mentioned before, tractography is a method for reconstructing fiber from tensor field. The main aim is to register this tractography directly known by streamline registration, that means register the streamline themselves at the native space. Here the directional and connectivity information remains same as diffusion tensor image, because the streamline is reconstructed from tensor images. This streamline registration could be classified in two different ways: one is point based where each streamline is considered as a set of points and another is streamline-streamline (fiber-fiber) registration.

For point based approach [18], spatial coordinate sequence is used to represent the streamline. Points are represented in high dimensional point space. Efficient Interactive Closest Feature point (ICF) is used to register different tractographies. Computational complexity on high dimensional search is handled by implementing approximate nearest neighbors techniques. This method is worked for inter subject and demonstrated with the preselected bundle (bundle of interest).

In multi-scale framework [11], curvature and torsion features are used to represent each streamline. Different tractographies are co-registered by using the global rigid transformation with Procrustes analysis. Mean square difference has been used as similarity measure. The method tried to match each streamline individually that makes the method computationally expensive. This method is demonstrated for intra subject registration.

Another type of streamline registration is used in [19], where streamlines are projected on high dimensional feature space with a 3D coordinates sequence. Fiber model is extracted by adaptive mean shift (AMS) clustering. Gaussian Mixture Model (GMM) is represented by assigning weight to each fiber model. The registration is performed as the alignment of two GMMs by maximizing the correlation ratio. Current based registration [20] are also used where fiber are represented as current. Recently another unbiased multi-subject registration is proposed in [21]. In that paper registrations are done by minimizing the entropy based objective function. Distance between the streamlines are calculated and represented by the gaussian kernel distribution. This registration technique works with the whole brain with group wise registration.

3 Problem Statement

In medical image registration, especially MRI (magnetic resonance imaging) registration plays a vital role due to different types of acquisition techniques and equipments. From the very beginning it was just image based registration where two images are try to overlap and find the differences. The differences are tried to understand by the naked eye.

With the growing preprocessing of dMRI data, Diffusion tensor image (DTI) are introduced and then the same image based registration technique is used on DTI data. By the same way when tractography data is introduced as the 3D structure, then again focus shifted on the registration technique. Because, tractography is different types of information about neuron and the main focus is based on directly register this tractography without any anatomical information. Actually for the tractographiy data registration, no transformation is meaningful since it is not possible to reconcile two different anatomies by means of rigid (or non-rigid) transformations.

Also recent methods are voxel based and computationally very expensive due to voxel to vexel similarity measuring cost. And as it calculates the spatial transformation iteratively, it could suffer for local optima. That's why the concept of streamline-streamline registration comes on the mind of researchers as the quality being optimized during registration are closely related to final goal of streamline registration. When we use the voxel based method, we have information about one voxel, but a streamline (i.e, its a set of voxel information) could be used for registration techniques. Hence, the problem is how to use the streamline information to register the whole brain tractrography. There is no general framework available regarding the problem. Another problem with streamline registration method is limited by subject-subject (pairwise) registration. But for segmentation, more than one subject is needed to be registered.

Fig. 3 demonstrates the overall concept of tractography registration both in image and streamline based. The solid lines show how images are converted from native to common space. Afterward, the affine transformation is used to wrap tractography in common space that is illustrated in the right upper corner of the figure. Now our goal is to avoid all those transformations and register directly from tractography to tractography (native space) with one conversion referred by dotted arrow in the figure.

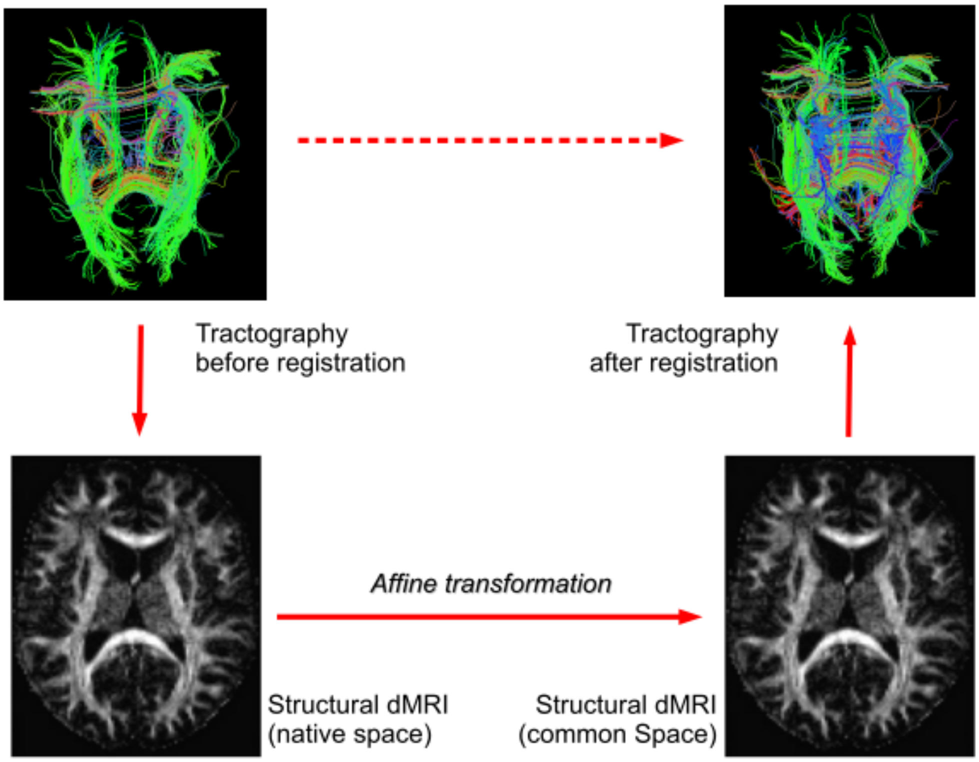

Fig. 3. Tractography registration

Additional to the above mentioned problem, we need to handle huge computational expenses in a very efficient way. Because one brain has almost three million tracts, so it's not easy to find the same tract on different brains.

4 Proposed Solution

All the streamline or direct registration technique that was proposed based on linear transformation that includes translation, rotation, scaling and other affine transformation. Our main goal is not to use any kind of transformation. The idea is to use the mapping technique, more specifically use the graph kernel concept for tract matching. The idea of mapping is to match a target streamline from more than one different brain without any references. This may be done with rigid or non-rigid transformations, but here we are interested in a different and indirect approach that does not require such transformations. In this case we could use the concept of graph kernel for nearest neighbor classification.

Every registration based on three different parts:

- transformation
- the registration paradigm (similarity measure)
- the optimization procedure

If we tried to put our proposed method on this three different parts then first we don't want to any transformation described above. For the second part i.e., similarity measure, measuring similarity of Graph Nodes by Neighbor Matching could be used. And for the optimization process, distance matrix among streamlines could be used.

Our proposed method will be used with the dissimilarity representation [22] of the whole brain to represent the streamline or streamline in vectorial space. The method will also be used to calculate the distance between the streamline or streamline. In this case different distances calculation are proposed in different literatures and modified Hausdorff distances [23] will be used to calculate the distance of streamline.

5 Conclusion

Registration of dMRI image is the key component for the dMRI data analysis. Here tractography comes as an advanced level of representation of dMRI data and analysis of tractography has been noticed by the machine learning and pattern recognition communities. But for the segmentation purpose especially for supervised segmentation its necessary to put all subjects in a common space and image based registration was the process to do the registration. Later some streamline based registration methods are proposed, but they were mostly based on specific bundle, not for the whole brain. The method also has the limitation of subject-subject registration problem. Our main to goal is to use the non-linear streamline based registration technique for the whole brain. Additionally our focus will be based on the multi-subject brain registration. A good and appropriate registration helps to segment the bundle of tracts more preciously and it is very helpful for surgical and disease identification.

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