Simultaneous segmentation and distortion correction on diffusion weighted MR using shape priors

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Abstract In whole-brain connectivity analysis of diffusion weighted MR images (DWI), an accurate delineation of the white-matter and grey-matter surfaces is required. While high-standard segmentation is readily available for anatomical MRI, such as T1-weighted, DWI typically have drastically lower resolution and strong geometrical distortions. We propose a DWI segmentation-registration framework that exploits the detailed anatomy extracted from anatomical MRI as shape-prior. We use an "active contours without edges"-like model to look for a deformation field that optimally maps the shape prior on the multivariate features in diffusion space. This joint approach reflects the intrinsic coupling of segmentation and distortion correction. Complementary, a precise and consistent cortical parcellation on DWI is straightforward by projection from T1 space. Thus, we expect to improve the reliability and robustness of the resulting connectivity networks and their comparability within and across subjects. Preliminary results on synthetic datasets and simulated DWI confirm the effectiveness of our approach.

Keywords: diffusion weighted imaging, connectomics, echo planar imaging, magnetic resonance, segmentation, registration, distortion correction

1 Introduction

Diffusion Weighted Imaging (DWI) is a widely used family of Magnetic Resonance (MR) techniques [17] which recently has accounted for a growing interest in its application to whole-brain structural connectivity analysis. This emerging field, coined in 2005 as *MR Connectomics* [5, 16], currently includes a large amount of imaging techniques for acquisition, processing, and analysis specifically tuned for DWI data.

The whole-brain connectivity analysis has arisen some challenges that should be overcome in order to get reliable structural information about the neuronal tracts from DWI [11, 12]. The earlier stages of these processing pipelines generally include two necessary steps, brain tissue segmentation on the diffusion space and the correction of geometrical distortions inherent to the imaging techniques [6].

In this work, we will refer as brain tissue segmentation to the precise delineation of the cerebrospinal fluid (CSF)-Grey Matter (GM) and GM-White Matter (WM) interface surfaces. This segmentation is an important step on which strongly rely further tasks. In tractography, a high-standard WM mask is required. Otherwise, there is an important risk for the algorithm to lose fiber bundles. This requirement is usually solved in practice by plainly thresholding the fractional anisotropy (FA) (a well-know scalar map derived from DWI which depicts the isotropy of water diffusion inside the brain). Additionally, a precise location of the GM-WM surface is required in the final steps to achieve a consistent parcellisation of the cortex to represent the nodes of the output network. This parcellisation is generally defined in a high-resolution and better understood structural Magnetic Resonance Imaging (MRI) of the same subject (e.g. T1 and/or T2 weighted acquisitions). Conversely, this problem is resolved with non-linear registration of a structural MRI of the subject to the DWI data. Even though some efforts have addressed the study of the robustness of tractography versus the intra-subject variability [20, 7], the results produced are restricted to relevant regions of the brain. Therefore, extremely robust and precise segmentation methods are required in the whole-brain application.

On the other hand, the DWI data is usually obtained with echo-planar imaging (EPI) acquisition techniques, that often suffer from severe distortions due to local field inhomogeneities. Generally, it is easily appreciated in the anterior part of the brain, along the phase-encoded direction. Some methodologies have been developed and generically named as *EPI-unwarp* techniques [8, 9, 10, 15]. They usually require the extra acquisition of the magnitude and phase of the field (field-mapping), condition which is not always met. Some other methodologies do not make use the field-mapping, compensating the distortion with non-linear registration from structural MRI or other means [1]. To our knowledge, there exists no study of the impact of the EPI distortion on the variability of tractography results.

In this paper we propose a novel registration framework to simultaneously solve the segmentation and distortion challenges, by exploiting as strong shape-prior the detailed anatomy extracted from anatomical MRI. This is justified by the strong relationship between both problems, and the advantage of a significant increase of coherence among these steps in the complete processing pipeline. We reformulate the segmentation problem as an inverse problem, where we seek for an underlying deformation field (the distortion) mapping from the structural space into the diffusion space.

2 Methods

2.1 Simulated datasets

As described in section 1, the general situation in the connectivity pipelines consists on having a reliable segmentation obtained from the high resolution T1-weighted (T1) reference image. Therefore, a precise location of the tissue interfaces of interest is available in a reference space. Given that there is no interest on the anatomical reference segmentation, we directly obtained the shape priors from the models.

On the other hand, the target DWI data is characterized by its low resolution (typically around $2.2x2.2x3mm^3$). Depending on the posterior reconstruction methodology and the angular resolution intended, the DWI raw data has to be processed in order to extract the information in a manageable manner. Particularly, we will use the FA and mean diffusivity (MD) maps for convenience. Whereas FA describes the *shape* of diffusion, the MD depicts the *manitude* of the process. There exist two main reasons to justify their choice. First, they are well-understood and standardized in clinical routine. Second, together they contain most of the information that is usually extracted from the DWI-derived scalar maps.

In order that demonstrating the functionality of the proposed methodology and characterize its possibilities, we developed two synthetic models and simulated their corresponding DWI raw signal as described in [19]. (HERE WE NEED A GOOD DESCRIPTION OF THE DATA, directions, resolution, etc) . The first model consists of several spherical shapes emulating the different brain tissues (see Figure 1, first row). The second model is based on the BrainWeb dataset. We reconstructed the DWI signal with standard procedures to approximate the environment to the real one at maximum.

2.2 Active Contours without edges-like variational segmentation model

Let us denote $\{c_i\}_{i=1..N_c}$ the nodes of a shape prior surface. In our application, a precise WM-GM interface extracted from a high-resolution reference volume. All the formulations can be naturally extended to include more shape priors. On the other hand, we have a number of DWI-derived features at each voxel of the volume. Let us denote by x the voxel and $f(x) = [f_1, f_2, \dots, f_N]^T(x)$ its associated feature vector.
The transformation from reference into DWI coordinate space is achieved through a dense deformation field $u(x)$, such that:

$$c'_i = T\{c_i\} = c_i + u(c_i) \tag{1}$$

Since the nodes of the anatomical surfaces might lay off-grid, it is required to derive $u(x)$ from a discrete set of parameters $\{u_k\}_{k=1..K}$. Densification is achieved through a set of associated basis functions Ψ_k (e.g. rbf, interpolation splines):

$$u(x) = \sum_k \Psi_k(x) u_k \tag{2}$$

Consequently, the transformation writes

$$c_i' = T\{c_i\} = c_i + u(c_i) = c_i + \sum_k \Psi_k(c_i) u_k \tag{3}$$

Based on the current estimate of the distortion u, we can compute "expected samples" within the shape prior projected into the DWI. Thus, we now estimate region descriptors of the DWI features $f(x)$ of the regions defined by the priors in DWI space. Using Gaussian distributions as region descriptors, we propose an Active Contours without edges (ACWE)-like, piece-wise constant, variational image segmentation model (where the unknown is the deformation field) [3]:

$$E(u) = \sum_{\forall R} \int_{\Omega_R} (f - \mu_R)^T \Sigma_R^{-1} (f - \mu_R) dx \tag{4}$$

where R indexes the existing regions and the integral domains depend on the deformation field u. Note that minimizing this energy, $\operatorname{argmin}_u\{E\}$, yields the maximum a posteriori (MAP) estimate of a piece-wise smooth image model affected by Gaussian additive noise. This inverse problem is ill-posed [2, 4]. In order to account for deformation field regularity and to render the problem well-posed, we include limiting and regularization terms into the energy functional [13, 18]:

$$\begin{aligned} E(u) = &\sum_{\forall R} \{ \int_{\Omega_R} (f - \mu_R)^T \Sigma_R^{-1} (f - \mu_R) dx \} \\ &+ \alpha \int \|u\|^2 dx + \beta \int \left(\|\nabla u_x\|^2 + \|\nabla u_y\|^2 + \|\nabla u_z\|^2 \right) dx \end{aligned} \tag{5}$$

These regularity terms ensure that the segmenting contours in DWI space are still close to their native shape. The model easily allows to incorporate inhomogeneous and anisotropic regularization [14] to better regularize the EPI distortion.

At each iteration, we update the distortion along the steepest energy descent. This gradient descent step can be efficiently tackled by discretizing the time in a forward Euler scheme, and making the right hand side semi-implicit in the regularization terms:

$$\frac{u^{t+1} - u^t}{\tau} = -\sum_{i=1}^{N_c} \left[\Delta E(f(c_i')) \hat{n}_{c_i'} \Psi_{c_i}(x) \right] - \alpha u^{t+1} + \beta \Delta u^{t+1} \tag{6}$$

where the data terms remain functions of the current estimate u^t, thus $c_i' = c_i'(u^t)$. For simplicity on notation, we restricted the number of priors to only 1. We also defined $\Delta E(f(c_i')) = E_{out}(f(c_i')) - E_{in}(f(c_i'))$, and $E_R(f) = \sqrt{(f - \mu_R)^T \Sigma_R^{-1} (f - \mu_R)}$. We applied a spectral approach to solve this implicit scheme:

$$u^{t+1} = \mathcal{F}^{-1} \left\{ \frac{\mathcal{F}\{u^t/\tau - \sum_{i=1}^{N_c} \left[\Delta E(f(c_i')) \hat{n}_{c_i'} \Psi_{c_i}(x) \right] \}}{\mathcal{F}\{(1/\tau + \alpha) I - \beta \Delta\}} \right\} \tag{7}$$

2.3 Experiment

For both models, we created manually a sound distortion visually similar to real EPI distortions. We interpolated the distortion to a dense deformation field, necessary for warping the raw DWI simulated data. Once the signal was deformed, we proceeded to reconstruct the Diffusion Tensor Imaging (DTI) and subsequently obtained the scalars of interest (FA, MD) and estimated their parameters on the model.

We evaluate the performance of our methodology to estimate the deformation field and compare it to the original synthetic deformation field applied to the data.

3 Results and discussion

The proposed method successfully reverted the synthetic distortion field we applied to the data. With 16x16x16 control points, the displacements field is dense enough to correctly represent the synthetic field. (INCLUDE FIGURE). Figure XX shows the restored image and a difference map with the original model (we can also compute Dice indexes and that stuff).

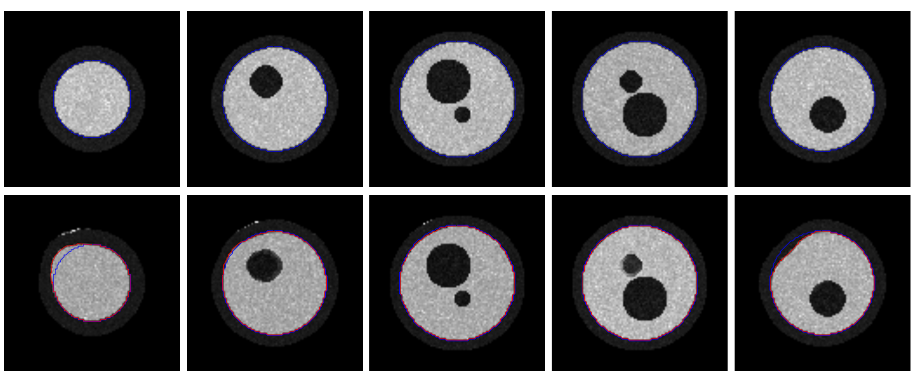

Figure 1. First row presents several slices along Z axis of the FA map obtained after DTI fitting (using the original signal without simulated distortion) and the corresponding WM-GM contour. Second row contains the warped FA map (using the distorted signal). The red contour corresponds to the interface detected after registration. In blue color, the initial WM-GM contour (the same as in previous row).

4 Conclusion

A novel application for the ACWE framework is proposed, with the aim at recovering the displacement field underlying the EPI geometrical distortions. Exploiting the segmentation properties of the ACWE and optimizing the displacement field, we describe a registration-segmentation methodology that simultaneously segmented and restored the distortion on DWI-like synthetic data. Visual results and quantitative results are provided.

Once proven the aptness of the methodology to the application with simplistic synthetic data, in further studies we will cover the actual performance on real images and the benefits of overcoming the described challenges (segmentation and EPI distortion correction) in one single step.

We conclude stressing on the importance of tackling with the numerous challenges that exist on the DWI data processing in order to achieve reliable results on the whole-brain connectivity analysis.

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