Predicting T1 information from diffusion image data

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Introduction: Diffusion-weighted imaging (DWI) provides intricate details about the neural architecture of the brain. It is used to infer neural tracts, which are a macroscopic representation of the underlying neuronal bundles, using tractography methods [1]. Several scalar measures, such as, fractional anisotropy (FA) or entropy or kurtosis [2] have been proposed, not only for neuroimaging studies, but also for a better visualization of the underlying tissue types. However, none of these measures provides a clear contrast between gray matter, CSF and white matter with complex fiber crossings. On the other hand, a T1-weighted image has been widely used to delineate the different tissue types in the brain. However, many DWI neuroimaging studies either do not acquire a T1-weighted image or if they do, they acquire them at a different spatial resolution than the DWI images. Thus, they cannot be directly used in visualization of the fiber tracts (as background). One approach to address this issue has been to perform a mutual-information based registration of the T1-weighted image to the baseline B0 images in the DWI space. However, due to the EPI distortions in the DWI images and the fact that the baseline image (B0) itself has poor contrast between the different tissue types, it becomes challenging to register the T1-weighted image to the B0 images. In this work, we propose a machine learning based method to predict a T1-weighted image from novel rotationally invariant features of the diffusion profiles obtained from a DWI scan. There are several applications of this technique: namely, 1) as a proper background to visualize neural fiber tracts, and 2) in segmentation of cortical or sub-cortical gray and white matter regions using existing software such as Freesurfer, which requires a T1-weighted image and 3) in creating an accurate DWI atlas, so that cortical features are better preserved during non-rigid registration [3].

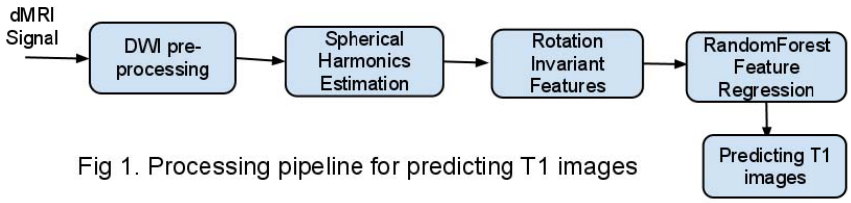

Fig 1. Processing pipeline for predicting T1 images

Method: The overall methodology of the proposed approach is given in the Figure 1. The diffusion weighted images are pre-processed to remove head motion, eddy current and EPI distortions. Next, an order 6 spherical harmonic (SH) basis is used to fit the signal at each voxel. Since, the T1-weighted image displays the different tissue types independent of the orientation, we would like to compute features of white matter that are rotation invariant. In general, the SH coefficients are not rotationally invariant, however, since the SH basis elements of different orders are mutually orthogonal, the L2 energy of SH coefficients corresponding to different orders is indeed invariant under arbitrary rotations. This fact allows us to define an $L = \lfloor N/2 \rfloor + 1$ dimensional vector $f = [f_0\ f_2\ ..f_L]$, of rotationally invariant Fourier signatures, given by :

$$f_n = \frac{1}{2n+1} \sum_{j=-n}^{n} |c_{n,j}|^2$$

These features are computed for every voxel in the brain. Next, a tree ensemble based Random Forest [4] method is used to learn the mapping between these Fourier features and the voxel values in a T1 image. The Random Forest method is a robust statistical learning method often used in machine learning due to its superior generalization capability and ability to avoid overfitting. In this work, we selected certain white matter (40 different ROIs), gray matter (39 ROIs) and 2 CSF (ventricles) regions of a single subject as training set for the learning algorithm. Prediction was done on the same subject as well as other unseen subjects and a corresponding T1 weighted image was constructed. A similar strategy could be used to predict the T1 images from a DTI image, with the eigenvalues forming the rotationally invariant features. The predicted images are then anisotropically smoothed using a mean curvature based partial-differential-equation (PDE) for better visualization [5].

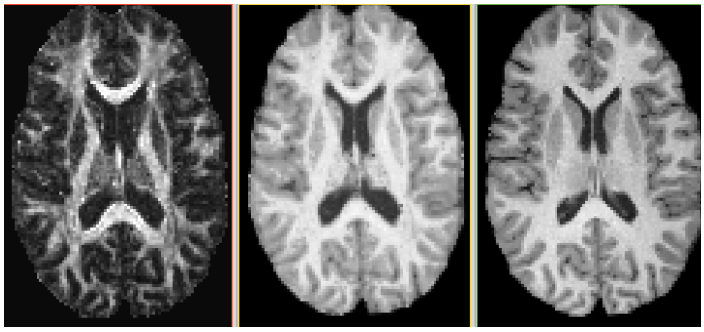

Fig2. Notice that FA does not provide a good contrast between gray and CSF areas. However, the predicted T1-like image is very similar to the actual T1 image shown in the right.

Results: The following figure 2 shows an axial slice of the predicted T1 image, the actual T1 image and the traditionally used FA map. In this case, the nonlinear map between the rotationally invariant SH features and the T1 image was learnt from one subject and prediction was performed on a new (unseen) subject. As observed, the contrast in the predicted T1 is very clear between the gray and CSF areas. Also notice the clear prediction of white matter in the region of fiber crossings. Thus, this image can serve as a better background for tract visualization. Further, the predicted T1 images can be used in registration algorithms as well as in creating DWI atlases (instead of using the FA maps). Further, Freesurfer (surfer.nmr.mgh.harvard.edu) can now be used directly in the DWI space for parcellation. On a more quantitative note, the normalized mean squared error (over 10 subjects) between the actual T1 image and the predicted T1 image is around4.59%.

References: [1] Malcolm, J.G., Shenton, M.E., Rathi, Y.: Filtered Multi-tensor Tractography. IEEE Trans. On Medical Imaging 29, 2010. [2] Ozarslan, E., Vemuri, B., Mareci, T., 2005. Generalized scalar measures for diffusion MRI using trace, variance, and entropy. Magnetic Resonance in Medicine 53 (4), 866–876. [3] Zollei, L., Stevens, A., Huber, K., Kakunoori, S., Fischl, B., 2010. Improved tractography alignment using combined volumetric and surface registration. Neuroimage 51, 206–213. [4] Breiman, Leo (2001). "Random Forests". *Machine Learning* **45** (1): 5–32. [5] Tannenbaum A.: Three snippets of curve evolution theory in computer vision, Mathematical and Computer Modeling, 24, 103-119, 1999.