Mask-Based Motion and Eddy-Current Correction of High b-value Diffusion-Weighted Images

David Raffelt[1,2], J-Donald Tournier[1,3], Olivier Salvado[2], and Alan Connelly[1,3]

[1]*Brain Research Institute, Florey Neuroscience Institutes, Melbourne, VIC, Australia,* [2]*The Australian E-Health Research Centre, CSIRO, Brisbane, QLD, Australia,* [3]*Department of Medicine, University of Melbourne, Melbourne, VIC, Australia*

Introduction: Tractography [1] and voxel-based analysis [2] of diffusion-weighted images (DWI) benefit from higher-order models [3] that can resolve multiple fibre populations within a single voxel. Higher-order models require the acquisition of DWI with a high number of diffusion orientations, leading to relatively long scan durations (ca.10min) that increase the likelihood of subject motion. A common approach to correct for DWI motion artefacts involves rigid-body registration of each DW volume to a common b=0 image. A mutual information based metric is commonly used for the registration process due to the differing contrasts between the DW data and the b=0 image [4]. However, this approach is not sufficiently robust for correcting high b-value data acquired for higher-order models, due to the low signal-to-noise ratio (as illustrated in Fig. 2a). Furthermore, high b-value DWI is more prone to eddy-current induced distortions due to longer gradient pulse durations [5]. In this work, we describe a robust method to correct both motion artefacts and eddy-current induced distortions in high b-value data. The proposed method optimises two transformation models, and thus allows DW gradient vectors to be reoriented based on the rigid body (motion) component alone, without undue influence from the eddy-current components.

Methods: Image registration is performed using a whole-brain mask computed from each DW volume. Using a mask eliminates noise and gradient-direction dependent information, and therefore registration is based entirely on the spatial extent of the brain. Each DW mask was computed by thresholding the DWI using the parameter free method described in [6]. Spurious mask voxels due to background noise were removed by retaining only the largest connected-component of the mask. Holes within the mask were subsequently 'filled' by inverting the mask, retaining the largest connected-component (the background), then inverting once more. To fill any remaining holes that were connected to the background, we performed a dilation followed by an erosion. All DW masks were aligned using the following 7 steps (implemented using ITK [7]). **1)** Each DW mask was rigidly registered (rotation and translation) towards a template (computed as the average DW mask). **2)** Registered DW masks were then averaged and used to update the template. **3)** Given the current estimate of the rigid transformations, eddy-current transformation parameters (a scale and two shears along the phase encode direction) were estimated to minimise the distance between corresponding mask edge locations using a least squares fit. **4)** Compose rigid and eddy-current transformations. **5)** Update the template using the composite transforms. **6)** Repeat steps 1-5 until convergence (using the composite transformations). **7)** Apply estimated transformations to DW images, modulating the intensity by the scale factor in the eddy-current transformations. **8)** Reorient gradient directions using the rigid transformations [8].

To validate the proposed method, we generated a simulated DW dataset by first computing a population-average fibre orientation distribution (FOD) atlas from 24 DW images (8 subjects, 3 repeats, Siemens 3T Trio, b=3000 s/mm^2, 2.5mm isotropic) [3,9,10]. A spherical convolution was performed on the FOD atlas to obtain an estimate of the DW signal at each voxel. The DW signal (represented using spherical harmonics) was sampled along 60 directions to obtain a relatively noise-free DW dataset. Twenty different DW datasets were then generated, each with randomly added motion (±3° rotation and ±4mm translation for each axis) and eddy-current distortions (±0.05 scale and shear). Various amounts of Rician noise were added to each dataset (defined as the b=0 white matter signal-to-noise ratio (SNR)). The proposed method was used to correct each dataset and the performance was assessed using two measures: 1) The mean pair-wise Euclidean distance between 'corresponding points' across DW volumes, averaged over all voxels in a brain mask, 2) The mean angular error of all corrected gradient directions relative to the corresponding ground truth gradient directions.

To qualitatively assess the proposed method on *in vivo* DWI, data were obtained from a single subject using a Siemens 1.5T Sonata (81 directions, b=3000 s/mm^2, 2.5mm isotropic, SNR=14). We compared the proposed mask-based motion correction (with and without eddy-current correction) to a commonly-used method (DW to b=0 mutual information based registration, using both rigid and affine transformations). Methods were assessed by a visual comparison of the sharpness of the average of all DW volumes.

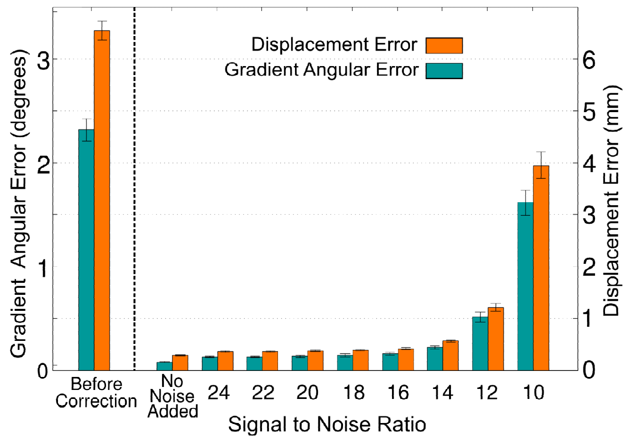

Figure 1. Validation of the proposed method using a simulated DWI with various levels of added Rician noise.

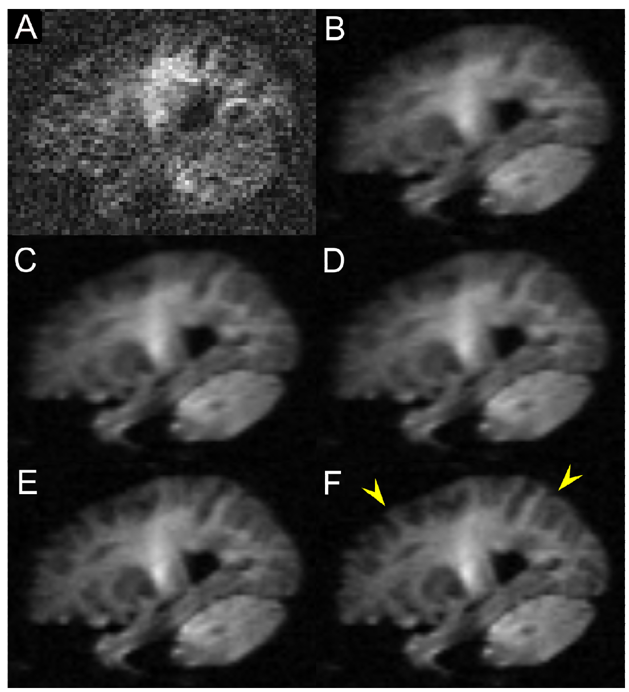

Figure 2. A) An example high b-value, low SNR, DW volume from the qualitative experiment. **B)** The mean of all 81 DW volumes, before correction. **C)** Mutual information rigid registration to a b=0 image. **D)** Mutual information affine registration to a b=0 image. **E)** After mask-based rigid body motion correction only. **F)** After mask-based motion and eddy-current correction.

Results: As shown by Fig. 1, within the typical SNR range (>14), the proposed method corrects the added motion and eddy-current artefacts with sub-voxel accuracy. Fig 2 illustrates the qualitative results *in vivo*. As seen in Fig. 2b, the mean DW image prior to correction is considerably blurry. However, as shown in Fig. 2e, the mean DW images are appreciably sharper following mask-based rigid body correction, with further improvement evident with the addition of eddy-current correction (Fig. 2f). This can be appreciated particularly in the regions indicated by the yellow arrows. For comparison, Fig.1c-d show results from mutual information based b=0 motion correction; it is clearly evident that these approaches did not improve the sharpness of the mean DW image to the same extent as the proposed mask-based method.

Discussion & Conclusion: We have presented a novel method to correct motion artefacts and eddy-current distortions using a DW mask-based registration towards the average DW mask. Validation using a simulated DW dataset suggests that the proposed method can accurately correct b=3000s/mm^2 data assuming typical noise levels and application to *in vivo* data demonstrate marked improvements in image contrast.

References: **[1]** Fillard, P et al. NeuroImage 56(1): 220-34 (2011) **[2]** Raffelt, D et al. (*in press*) doi:10.1016/j.neuroimage.2011.10.045 **[3]** Tournier, J-D et al. Neuroimage 35: 1459-72 (2007) **[4]** Rodhe, G et al. MRM 51(1):103-14 (2004) **[5]** Jones, D et al. NMR in Biomed 23(7):803-20 (2009) **[6]** Ridgway, G et al. NeuroImage 44(1):99-111 (2009) **[7]** Insight Toolkit www.itk.org **[8]** Leemans, A et al. MRM, 61(6):1336-49 (2000) **[9]** Raffelt, D et al. NeuroImage 56(3):1171-80 **[10]** MRtrix. *www.brain.org.au/software/*