An Algorithm for Moment-Based Global Registration of Echo Planar Diffusion-Weighted Images

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Introduction

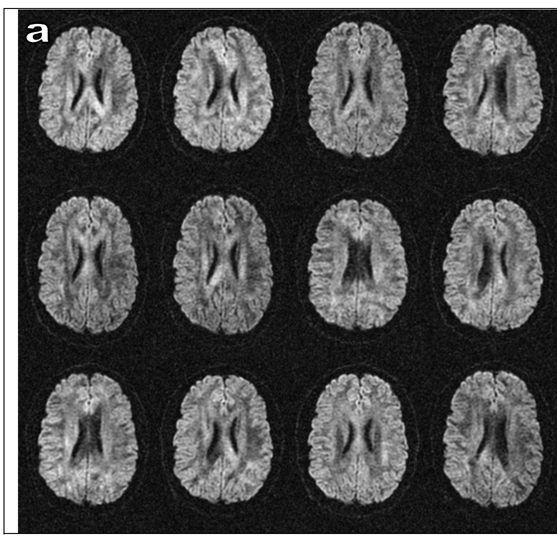
In a diffusion-weighted imaging experiment, the strong diffusion-sensitizing gradients can induce eddy currents, which will lead to image distortions in echo-planar images [1,2]. These distortions are typically represented with a 3-parameter model: scaling, translation, and shear along the phase-encoding direction. In diffusion-tensor MRI (DTI), these distortions will be different for each diffusion encoding direction and diffusion-weighting, leading to misregistration and errors in images calculated from two or more diffusion-weighted images (e.g., FA and trace{**D**}). A variety of methods have been proposed to correct or minimize the distortion effects including modifying the diffusion gradient waveforms [4], gradient amplifier pre-emphasis settings [6], distortion measurements in a phantom [5], and registration and modeling of the distortion [1, 3]. The latter approach is sensitive to the selection of a reference image for registration [1,5] and can be very complex if motion is also considered [3]. We have developed a novel fast and robust algorithm for the correction of eddy current distortions in diffusion-weighted images. The algorithm measures between-image distortions using low order moments of segmented diffusion weighted images, leading to a per-slice estimate of a linear model **M** of the imaging distortion. **M** maps from the diffusion-sensitizing gradient direction to the three parameters of the resulting eddy-current distortion.

Methods (Algorithm)

The algorithm can be summarized as: **(1)** Brain Segmentation: The brain is segmented from the background by thresholding and a combination of 2D and 3D connected components [7], creating a binary image mask. **(2)** Calculation of Moments and Transforms: Moments are a robust descriptor of object shape [8], calculated with $m_{ab} = \sum (x - \langle x \rangle)^a (y - \langle y \rangle)^b$ for (x,y) within the binary image mask of the brain. The scale S and shear H components of the transform can be recovered from m_{20}, m_{11}, and m_{02} with $S = \sqrt{(m_{20} m'_{02} - m'^2_{11}) / (m_{20} m_{02} - m^2_{11})}$ and $H = (m'_{11} - m_{11} S) / m_{20}$, with primed moments computed from the target image. Translation T is simply $\langle y' \rangle - \langle y \rangle$. The transform $\mathbf{W}_{ij}$ (consisting of H, S and T) from DWI i to j is calculated for all (i,j) pairs. **(3)** Modeling Distortion due to Eddy Currents: Note that $\mathbf{W}_{ij}$, is equivalent to $\mathbf{W}_j * \mathbf{W}_i^{-1}$, where $\mathbf{W}_i$ is the transformation from a reference image to image i. The transformation **W** due to eddy currents is modeled as a linear function of the diffusion-sensitizing gradient [1,3] via a 3x3 model matrix **M**: $[W] = [H \quad 1+S \quad T]^T = [M][G_x \quad G_y \quad G_z]^T$. This expression allows **M** to be estimated with an over-determined linear system of $\mathbf{W}_{ij}$, $\mathbf{G}_i$, and $\mathbf{G}_j$, with one row per (i,j) DWI pair. The process is repeated for each slice in the volume. **(4)** Warp Correction: By knowing the distortion model **M**, the transform $\mathbf{W}_i$ caused by gradient $\mathbf{G}_i$ can be determined from $\mathbf{M} * \mathbf{G}_i$ and the correction of image i is simply the inverse of $\mathbf{W}_i$. The non-iterative nature of this algorithm contributes to its speed. No single step in this method is particularly compute-intensive, the slowest step currently is segmentation.

Results & Discussion

An example of the correction results for a 3T DTI study with 12 DWIs are shown in Figure 1. Results for a 40-slice volume took approximately 5 minutes to compute on a commodity PC. Because $\mathbf{W}_i$ is the warp to DWI i from the reference image without eddy current distortion (since **M***0 is the identity transform), the distortion correction maps the DWIs onto the T2-w b=0 image (Fig. 1d) without ever having used the T2-w image as a registration reference. The T2-w image is a poor reference for intensity based registration with the DWIs because of basic differences in contrast (e.g. CSF) and asymmetric intensity variations due to anisotropy (white matter in DWI). The algorithm has been applied to both 1.5T (Utah) and 3T (Wisconsin) DTI studies with different encoding sets and appears to be quite robust. The accuracy of the algorithm depends on the accuracy of the brain segmentation and binary mask, although the use of all DWIs to estimate **M** imparts insensitivity to small errors in individual masks. Slice-to-slice consistency can be imposed by linear fitting of the distortion model **M** across all slices [e.g. 3]. Although the algorithm presented here is based on image moments from a binary image mask, the same distortion modeling and unwarping methodology could also be adapted to intensity-based image registration methods.



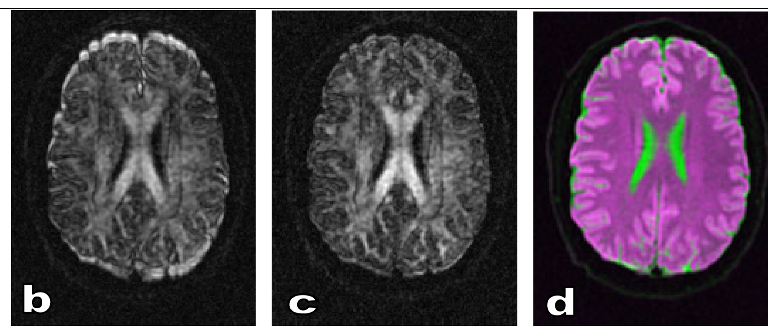


Figure 1. Correction of a single slice from a 39 slice, 12 encoding direction (a), b = 912 s/mm^2 diffusion tensor study performed on a 3T scanner. The misalignment is observed at the image edges in the RMS difference image shown in (b). After correction (c), the edge artifacts in the RMS difference image are clearly reduced and the tracts appear much sharper. One advantage of this approach is that the algorithm estimates the warp in each image from the T2-w reference image without actually using the T2-w image. After correction (d), the mean diffusion weighted image (purple) shows very good alignment with the T2-w reference image (green).

References:

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