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

G. Kindlmann[1], A. L. Alexander[2,3], M. Lazar[2,3], J. Lee[2], T. Tasdizen[1], R. Whitaker[1]

[1]Computer Science, University of Utah, Salt Lake City, UT, United States, [2]Medical Physics, University of Wisconsin, Madison, WI, United States, [3]W.M. Keck Lab, University of Wisconsin, Madison, WI, United States

Introduction

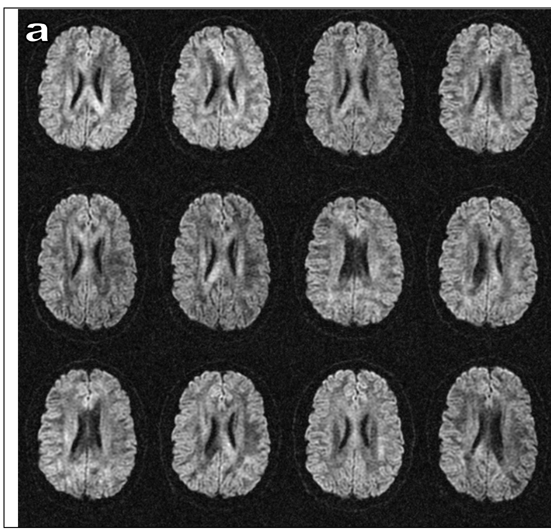
In a diffusion-weighted imaging experiment, the strong diffusion-sensitizing gradients can induce eddy currents, which will lead to image distortions in echo-planar images [1,2]. These distortions are typically represented with a 3-parameter model: scaling, translation, and shear along the phase-encoding 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.



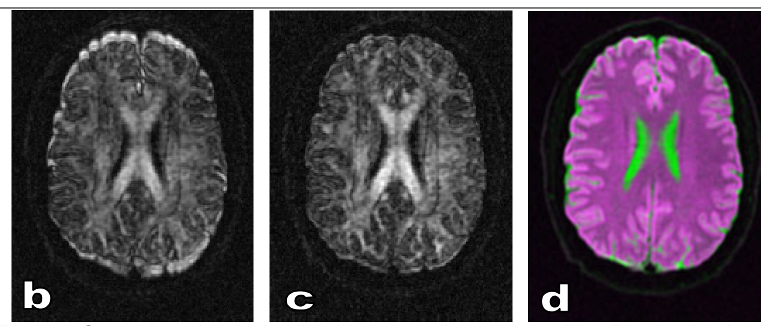


Figure 1. Correction of a single slice from a 39 slice, 12 encoding direction (a), b = 912 s/mm^2 diffusion tensor study performed on a 3T scanner. The misalignment is observed at the image edges in the RMS difference image shown in (b). After correction (c), the edge artifacts in the RMS difference 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).

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Moment-Based Global Registration of Echo Planar Diffusion-Weighted Images

G. Kindlmann[1], A.L. Alexander[2], M. Lazar[2], J. Lee[3], T. Tasdizen[1], R. Whitaker[1]

[1] Scientific Computing and Imaging Institute, University of Utah

Contact : Gordon Kindlmann gk@cs.utah.edu http://www.cs.utah.edu/~gk

[2] Department of Medical Physics, University of Wisconsin-Madison

[3] Utah Center for Advanced Imaging Research, University of Utah

Introduction

In diffusion-weighted imaging (DWI), the diffusion-sensitizing gradients can induce eddy currents, which distort the echo-planar images (EPI) commonly used in clinical diffusion studies of the human brain.

These distortions are typically characterized in terms of three degrees of freedom: **shear, scaling,** and **translation** along the phase-encoding direction [1,2].

In diffusion tensor MRI (DTI) [3], the eddy current distortions are different for each diffusion encoding direction and diffusion weighting. The resulting misregistration between DWIs leads to errors in tensor estimation and tensor attributes (anisotropy, principal eigenvector, etc.), and loss of effective resolution.

A variety of methods to minimize or correct eddy current distortion effects in EPI have been described. Bipolar diffusion-weighting gradients greatly reduce, but do not eliminate, eddy currents during EPI read-out [4]. Magnetic fields from eddy currents can be measured via field maps, though with increased acquisition time [2]. Phantom measurements can calibrate eddy current distortions in subsequent scans of human brains [5,6]. Correlation-based registration between the DWI and T2-weighted images is possible [1], though complicated by fundamental contrast differences (as in CSF) [7]. More sophisticated DWI registration methods have corrected both eddy current distortion and patient motion using the goodness-of-fit of the tensor model [8], or with a mutual information cost function to align DWI and T2 images [9].

We have developed a fast and robust algorithm for correcting eddy current distortions in DWIs, based on image **moments**, a statistical 2-D shape measure.

Calculating image moments of segmented DWIs enables recovery of the distortion transform between any two DWIs. From the ensemble of all pair-wise transforms, we linearly model the eddy current distortion as a function of gradient direction, so that the distortion present in each DWI can be calculated and removed.

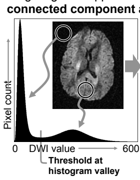
Although the T2 (non-diffusion-weighted) image is not used in this process, the method maps the DWIs to the undistorted coordinates of the T2-weighted image. It also generates scanner-specific information about the eddy current distortion, and its per-slice variations.

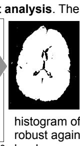
Outline of Algorithm

1) **Segmentation**: In each DWI, the brain interior is segmented from the skull and background.
2) **Transforms and Moments**: Moments are calculated from segmented DWIs, from which the distortion transforms between all pairs of DWIs are determined.
3) **Distortion Modeling**: The mapping between the direction of the diffusion-sensitizing gradient and the eddy current distortion is modeled as a 3x3 matrix.
4) **Model Fitting**: The previous steps are repeated on each slice of the image volume. Results may be improved at the top and bottom of the scan by fitting the model to a smooth variation across slices.
5) **Distortion Correction**: The distortion at each slice of each DWI is now known from the model. The DWIs are unwarped and resampled onto a common grid.

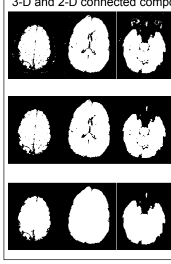
1) Segmentation

For each DWI, we generate a binary volume with value **1** inside the brain (including CSF in ventricles) and **0** outside. This allows the shape of the brain cross-sections in different DWIs to be compared readily, by removing intensity variations due to diffusion weighting. Our approach is a combination of **thresholding** and **connected component analysis**. The histogram of the DWI is typically bimodal: with a narrow peak for air, skull, and CSF, and a wide peak for the brain. A simple valley-finding algorithm finds a suitable global threshold value from the histogram of all DWIs. Moments are robust against small changes in region borders, so careful optimization of the threshold determination is not crucial.





The thresholded DWIs are then processed with a combination of 3-D and 2-D connected component analysis, as follows:



A) The single largest **bright 3-D** connected component is the brain. All smaller bright 3-D connected components (scalp, eyes, noise, etc.) are merged with the dark background.

B) Within each slice, the largest **dark 2-D** connected component is the background. All smaller dark 2-D connected components (CSF, noise) are merged with the brain. This completes our approximate segmentation procedure.

2) Transforms and Moments

To represent the eddy current distortions, we use a 2-D **homogeneous coordinate** transform in which **H**, **S**, and **T** are the shear, scale, and translate components of the distortion transform, respectively. The transform maps from (x,y) to (x′,y′):

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} x \\ Hx+Sy+T \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ H & S & T \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

X, y, and z axes are read-out, phase-encode, and slice selection, respectively. For brevity, we will notate the transform matrix as [H S T]. The inverse of [H S T] is $[H\ S\ T]^{-1}$ = [-H/S 1/S -T/S].

Moments are statistical descriptors of image shape [10], used in computer vision for tasks such as object recognition, object pose estimation, and registration, including estimation of affine transforms [11,12]. The 2-D moments μ_{ij} are defined in terms of summations over segmented DWI values *v(x,y)* in each slice:

$$\left.\begin{aligned} \langle x \rangle &= \frac{\sum x\, v(x,y)}{\sum v(x,y)} \\ \langle y \rangle &= \frac{\sum y\, v(x,y)}{\sum v(x,y)} \end{aligned}\right\} \text{Centroid of segmented image is (<x>,<y>)}$$

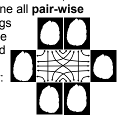
$$\mu_{ij} = \sum (x - \langle x \rangle)^i (y - \langle y \rangle)^j v(x,y)$$

We recover H,S,T through a relationship between the original moments μ_{02}, μ_{20}, μ_{11} and distorted image moments μ'_{02}, μ'_{20}, μ'_{11}:

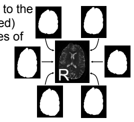
$$\begin{aligned} \mu'_{02} &= H^2\mu_{20} + S^2\mu_{02} + 2HS\mu_{11} \\ \mu'_{11} &= H\mu_{20} + S\mu_{11} \\ \Longrightarrow\ S &= \sqrt{\frac{\mu_{20}\mu'_{02} - \mu'^2_{11}}{\mu_{20}\mu_{02} - \mu^2_{11}}} \\ H &= \frac{\mu'_{11} - \mu_{11}S}{\mu_{20}} \\ T &= \langle y' \rangle - \langle y \rangle \end{aligned}$$

3) Distortion Modeling

With the image moments and the formulas above, we can determine all **pair-wise** mappings from one distorted DWI to another:



But we need to recover the mapping of each distorted DWI back to the (undistorted) coordinates of the T2-weighted reference image R:



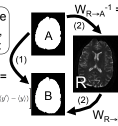
We accomplish this by modeling the relationship between the gradient direction **g** (associated with each DWI) and the induced eddy current distortion. Our linear model M has nine parameters:

$$\begin{bmatrix} H \\ S-1 \\ T \end{bmatrix} = \begin{bmatrix} \mathbf{h}\cdot\mathbf{g} \\ \mathbf{s}\cdot\mathbf{g} \\ \mathbf{t}\cdot\mathbf{g} \end{bmatrix} = \begin{bmatrix} h_x & h_y & h_z \\ s_x & s_y & s_z \\ t_x & t_y & t_z \end{bmatrix} \begin{bmatrix} g_x \\ g_y \\ g_z \end{bmatrix} = M\mathbf{g}$$

Without diffusion weighting, **g**=0, so there is no distortion in R. Given two DWIs A and B, and associated gradients $\mathbf{g}_A$ and $\mathbf{g}_B$, the distortion warping from A to B may be expressed in two ways:

(1) In terms of the known moments, as shown above:

$W_{A\to B}$ = [H S T] = $\left[\sqrt{\frac{\mu_{20}\mu'_{02} - \mu'^2_{11}}{\mu_{20}\mu_{02} - \mu^2_{11}}}\quad \frac{\mu'_{11} - \mu_{11}S}{\mu_{20}}\quad (\langle y' \rangle - \langle y \rangle)\right]$



$W_{R\to A}^{-1} = [\mathbf{h}\cdot\mathbf{g}_A\ \ \mathbf{s}\cdot\mathbf{g}_A+1\ \ \mathbf{t}\cdot\mathbf{g}_A]^{-1}$

(2) In terms of the known gradients $\mathbf{g}_A$,$\mathbf{g}_B$ and the **unknown** parameters **h**,**s**,**t** of model M.

$W_{R\to B} = [\mathbf{h}\cdot\mathbf{g}_B\ \ \mathbf{s}\cdot\mathbf{g}_B+1\ \ \mathbf{t}\cdot\mathbf{g}_B]$

That is, $W_{A\to B} = W_{R\to B}\, W_{R\to A}^{-1}$: warping from A to B is the same as undoing the warp from R to A, then warping from R to B. This leads to a system of linear equations of the model parameters **h**,**s**,**t** in terms of the moments and gradients. Every **pair** of DWIs contributes one equation to an over-determined system, solved with linear least squares, giving a per-slice distortion model M.

4) Model fitting

Smaller, more complex shapes in slices at the top of the cortex, and greater susceptibility artifacts at the bottom of the brain, are problematic for segmentation, degrading registration results. The physical origin of the EPI distortion, however, suggests smooth variation with slice position, as observed by others [8]. So that distortion estimates on some slices can improve estimates elsewhere, we quantify **segmentation uncertainty** on each slice in terms of the list of segmented DWI values $s(x,y)_i$ at location (x,y), using their standard deviation, normalized by their L2 norm, summed over the image:

$$\frac{\sum \mathrm{stdv}(s(x,y)_i)}{\sum \|s(x,y)_i\|_2}$$

After sorting slices by segmentation uncertainty, some fraction of the most "certain" slices are used to determine a **linear** fit of the nine parameter distortion model, as a function of slice position: **M(z)**. Future work will investigate higher-order fitting. The segmentation uncertainty can be inspected with $\mathrm{stdv}(s(x,y)_i)$:

Segmented DWI value s(x,y): stdv($s(x,y)_i$):

Low segmentation uncertainty ⇒ Slice **should** contribute to linear fit of M(z)

High segmentation uncertainty ⇒ Slice should **not** contribute to M(z)

5) Distortion correction

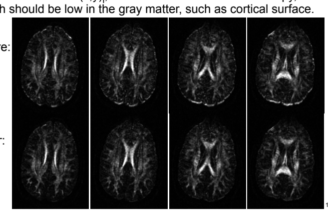
Having defined the distortion model as a linear function of slice position M(z), the EPI distortion in the DWI measured with gradient **g** is the [H S T] matrix found from M(z)**g**. Since distortion correction needs 1-D resampling along only the phase-encoding direction, we use a high-quality filter, such as a Hann-windowed-sinc kernel with 10 sample support, to better preserve small image features. Intensity is adjusted according to image scaling [9].

Results

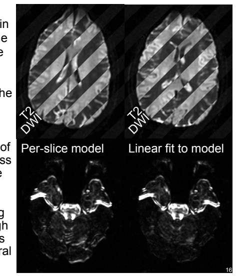
The corrections are small, so directly inspecting the pre- and post-registration DWIs is less informative than inspecting the **variance** of the DWI values $v(x,y)_i$, which is correlated with anisotropy, and which should be low in the gray matter, such as cortical surface.

Before:

After:



To assess whether the registration succeeded in mapping the DWIs to the undistorted space of the T2-weighted image, we interlaced the DWI **geometric mean** with the T2 image. The brain boundary and internal features match well. To determine the value of doing model fitting across slices, we inspected the DWI variance in a slice with high segmentation uncertainty. Model fitting improves the result. High "signal pile-up" corrupts the image at the temporal lobes, however.



Discussion

The computational simplicity of computing moments, transforms, and models allows this method to be extremely fast. **No iterative search or optimization is used**, and no additional calibration or phantom scans are needed. In the current implementation, the bottleneck is the DWI segmentation, not the registration itself. Robustness comes from using moments for shape measurement, the use of all DWIs simultaneously, and the model smoothing across slices. There is only one free parameter: the fraction of slices to use for estimating model variation across slices. Using as few as 50% of the slices (as above) generally produces good results. Because our method does not account for patient motion, motion will confound the model estimation, incorrectly ascribing all translation to eddy current effects, with the shape estimation degraded by image rotations. However, the underlying theory of using shape estimation techniques from computer vision to recover the parameters of a distortion model could likely be incorporated into a more complete registration framework [9].

Acknowledgements, URLS, References

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- http://teem.sourceforge.net : command-line interface to C implementation
- http://software.sci.utah.edu/scirun-biopse_1_20.html : GUI to C++ wrapper around C implementation, as well as various visualization and simulation tools
- http://www.sci.utah.edu/~gk/ismrm04/epi-moments.ppt : this poster

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