Accounting for Changes in Signal Variance in Diffusion Weighted Images Following Interpolation for Motion and Distortion Correction

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Introduction: Processing of clinical diffusion weighted images (DWIs) for Diffusion Tensor Imaging (DTI) and other applications requires correction for motion, eddy current distortions [1], and susceptibility induced EPI distortions [2]. These corrections are obtained by image registration techniques followed by interpolation of the original images. Image interpolation, however, alters the noise characteristics of the resulting diffusion image: in particular, the expected signal variance is no longer spatially homogeneous [3]. Not accounting for these changes in the intrinsic variance of the images may introduce spatial artifacts in tensor fitting, produce miscalculation in probabilistic tractography, and affect the outcome of robust tensor fitting methods like RESTORE [4]. In this work, we propose a method for accounting for signal variance changes in diffusion weighted images that underwent a series of distortion correction steps. We show the effects on images of the Chi-squared statistics of tensor fitting. This method is implemented in the software package TORTOISE [5] which is freely available for download (www.tortoisedti.org).

Methods:
Theory: In image registration, the output is a transformation map that maps the discrete voxel coordinates (x) of the final image (I_f) to the continuous coordinates (f(x)) of the original image (I). These continuous coordinates are fed to an interpolation procedure to obtain the final voxelwise intensities. Interpolation algorithms assign weights α_i on voxels w_i in the neighborhood Ω of f(x) and compute the final intensity as: $I_f(x)=\sum_{w_i\in\Omega}\alpha_i I(w_i)$
Rohde et al. [3] proposed a solution for the single transformation with trilinear interpolation case and stated that the signal variance due to noise after interpolation during a registration process can be expressed as:

$$Var(I_f(x))=\left(\sum_{w_i\in\Omega}\alpha_i^2 Var(I(w_i))\right)+2\left(\sum_{\{w_i,w_j\}\in\Omega, i<j}\alpha_i\alpha_j Cov(I(w_i),I(w_j))\right)=\sigma^2\left(\sum_{w_i\in\Omega}\alpha_i^2+2\left(\sum_{\{w_i,w_j\}\in\Omega, i<j}\alpha_i\alpha_j Corr(w_i,w_j)\right)\right) \quad (1)$$

In Equation 1, σ^2 signifies the noise variance of the original diffusion weighted image. The multiplier of σ^2 is the noise scale factor and is a function of the interpolation weights α_i, thus the transformation and voxel's signal correlations induced by the scanner during image reconstruction. This term states that the noise in the registered images is no longer spatially uniform and less than the original noise level. It can induce striping artifacts to the image noise levels in case of rotations and wavy striations with non-linear transforms. These patterns can be observed in Figure 1.

Data: The method is demonstrated on data acquired on one healthy subjects scanned with a 1.5T MR system (GE Medical Systems, Milwaukee, WI) with a single-shot spin-echo EPI sequence with FOV=20x20cm, slice thickness=4mm, matrix size=64x64, 39 axial slices. The DWI data set consisted of 4 low b-value images and 24 images with b=1000s/mm^2. Fast spin echo T2W images were also acquired as anatomical targets.

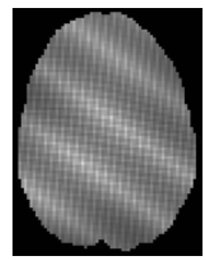

Figure1. Noise variance maps.

DTI Processing: All diffusion weighted images were first upsampled by a factor of two and corrected for motion and eddy-current distortions. Subsequently an additional EPI distortion correction step was performed. This correction was performed by elastically registering the first b=0s/mm^2 to its corresponding undistorted structural T2WI with B-Splines transformation of grid size 7x7x7. The computed deformation was applied to all DWIs belonging to the DWI dataset [4]. Finally, all the DWIs were transformed onto the structural image's space yielding four consecutive transformation applications. The diffusion tensors were computed twice using non-linear regression with the original uniform noise and with the spatially varying corrected variance. Chi-squared maps of tensor fitting were analyzed as quality metrics for the estimation process.

Noise Estimation Framework: Equation 1 cannot be directly be used to estimate the voxelwise noise variance in the presence of several transformations. Therefore, all the transformations of the processing pipeline were first successively applied to the coordinates to yield one deformation field that mapped the original image onto the final. Additionally, depending on the size of the interpolation kernel size (2x2x2 for trilinear, 4x4x4 for tricubic), correlations among the intensities of many voxels need to be estimated. These correlations are scanner and pulse sequence dependent. Two methods are proposed for this estimation: 1) The voxels containing real data are determined with brain extraction and skull stripping and are disregarded. The remaining noise image is translated and the Pearson's correlation is computed between the translated and the original image. 2) Based on a training set, the correlations were computed using the first method. We observed that the spatial correlations follow a Gaussian-like shape with a very steep steepest decrease along slice select direction and the least spatial decrease along phase encoding. These are in conformance with the findings of [3]. An anisotropic Gaussian like function was estimated from the training data correlations and is used for the new unobserved images. Both these methods can operate with any interpolation kernel and are both implemented in the TORTOISE package.

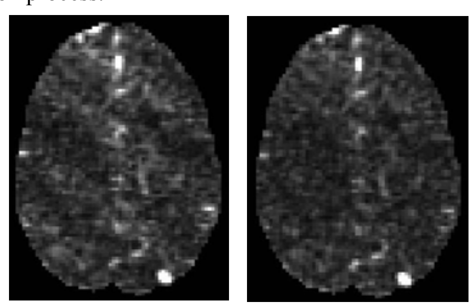

Figure2. Left: Chi squared maps using uniform noise. Right: Chi-squared maps using noise estimated with proposed method of

Results: Chi squared maps of tensor fitting with original uniform noise and noise patterns computed with Equation 1 are displayed in Figure 2. As can be observed from the left image, using the original spatially uniform noise results in striping artifacts in the tensor-fitting chi-squared map, and therefore second order tensor statistics. The striping artifact is not visible on the chi squared map in the right image, which was computed with the spatially varying noise pattern of Figure 1.

Discussions: In this work, we presented an algorithm included in the TORTOISE software package to estimate the noise variance after image based registration of DWIs. Our method is able to correct artifacts occurring due to consecutive application of several registrations and can compute spatial correlations for any interpolation kernel. For analysis on DTI using second order statistics, such as error propagation methods, statistical tests on populations, robust tensor fitting and probabilistic tractography, it is strongly advised to use the corrected noise variance for more accurate results.

References: 1. Rohde G et al., TBE, 2005;, **2**. Jezzard P. et al., Magn Reson Med ,1995;, **3**. Rohde G et al., Neuoimage, 2005;, **4**. Chang L, et al. Magn Reson Med 2005, 53:1088-1095. **5**. C.Pierpaoli et al; ISMRM,Stockholm,Sweden.2010 **6**. W u M. et al., ISMRM, 2007.