Mutual Information Estimation Using K-Space Data: An Application For Eddy-Current Distortion Correction In Diffusion Tensor Imaging

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Abstract: Mutual information between diffusion-weighted and T2-weighted images, used for eddy-current distortion correction in diffusion tensor imaging, is generally estimated using linear interpolation and partial volume methods. These methods compromise the values of the mutual information, thus providing reduced accuracy in eddy-current distortion correction parameters. To avoid these artifacts, we developed a method based on the shifting theorem, where a pixel value in any specific coordinate can be discovered using the Fourier transform of the phase-shifted raw data in k-space. The pixel value in a specific coordinate can be approximated by its nearest neighbor on an upsampled spatial domain to reduce the computational time. Parzen windows, i.e., a 2D Gaussian kernel, can be used to smooth the joint probabilities of the image pixel values in order to simplify the optimization procedure. The results after distortion correction were compared using variances of principal components of the image data set. Parametric images such as fractional anisotropy images and color maps of the brain white matter fiber orientation were also compared in terms of visual qualities. The results indicate major improvement of these parametric images after applying the proposed distortion correction method.

Introduction: Diffusion tensor imaging (DTI) has been explored in the past few years to study tissue water diffusion characteristics and tissue integrity in health and diseases. To estimate diffusion tensors, at least seven images are acquired at the same spatial location with different magnitudes and directions of diffusion-sensitizing gradients. These images are distorted by eddy current caused by residual gradients [1]. A popular scheme to correct these images involves optimization of distortion model parameters with respect to the mutual information (MI) cost function between diffusion-weighted images (DWI) and T2-weighted images (T2WI). This process involves image transformation and interpolation. Linear interpolation (LI) and partial volume (PV) methods were used by many research groups [2-4]. Both methods create artifacts in the MI cost function [5]. Whenever the transformation aligns two image grids, the LI and PV calculations are no longer required, causing a sudden change in the value of the measure. In this work, a method based on the shifting theorem (ST) was proposed to avoid these artifacts. The k-space data were phase-shifted and Fourier-transformed to recover a pixel value in any spatial coordinate. The number of image quantization levels (NQ) and the standard deviation (SD) of the Parzen window (PZ) were investigated to obtain optimal sets of these parameters. Images with and without corrections were compared using the pixel value variances of principal component analysis (PCA) components. The corresponding fractional anisotropy (FA) images and color maps of the brain white matter fiber orientation were also visually compared.

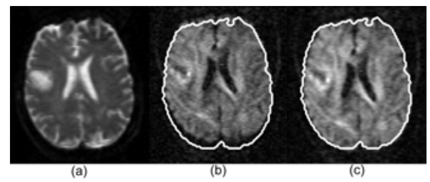

Figure 1: (a) A T2WI and DWI (b) before and (c) after correction. Solid white boundaries are brain boundaries extracted from T2WI.

Materials and Methods: Brain MRI was carried out on a clinical 1.5T whole-body MRI scanner (Magnetom Vision, Siemens Medical Systems) with a standard circularly polarized radiofrequency head coil. DTI data was acquired using a single-shot spin echo, echo planar imaging sequence (TR/TE = 5000/99 ms, 90° flip angle, 128×128 matrix size, 2×2×4 mm voxel size, one T2WI, 6 DWI with b = 1,000 s/mm^2, NEX = 12). A three-parameter distortion model [1] (i.e., shearing, scaling, and translation) was used. Powell's optimization algorithm with the Normalized MI (NMI) [6] cost function was applied. Pixel values of the DWI on a new coordinate were computed based on the shifting theorem applied in k-space, i.e., $s(x-\delta_x, y-\delta_y) \Leftrightarrow S(k_x, k_y)\exp(-j2\pi k_x\delta_x)\exp(-j2\pi k_x\delta_y)$. These pixel values can be also approximated using their nearest neighbors on an upsampled spatial domain to reduce the computational time. After transformation, the DWI pixel values were on the same grid as of the corresponding T2WI. The probabilities and joint probability of the image pixel values, i.e., histograms and joint histogram, were then calculated conventionally by counting the number of pixels in each quantization level. These probabilities were used to estimate the NMI [6]. After distortion correction, the T2WI from 12 repetitions were registered slice by slice using the Automated Image Registration (AIR) algorithm [7]. The same registration parameters from the AIR program were also applied to the DWI before averaging across 12 repetitions. The diffusion tensor for each image pixel was calculated by solving a set of linear equations [8].

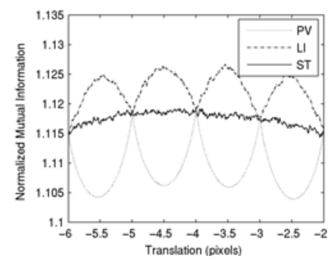

Figure 2: Plots of the NMI of the images in Fig. 1 vs. the translation in y axis using the PV, LI, and ST methods.

Results and Discussions: A T2WI and DWI before and after correction of a slice shown in Fig. 1. The DWI is distorted significantly with apparent translation along the y axis. Fig. 2 shows plots of the corresponding NMI vs. the translations (in pixels) on the y axis calculated using the PV, LI, and ST methods with the NQ = 128. The plots of the NMI using the PV and LI methods contain a ripple whenever the translation is an integer number of pixels. In contrast, the plot of the NMI using the proposed ST method does not have the ripples. Cases were examined when the NQ was equal to 128, 64, and 32 and the SD of the PZ was equal to 0.5, 1, 2, and 3. The results show that (1) reducing NQ smoothes the NMI plots and makes the global maximum more prominent; and (2) applying the PZ with an appropriate SD gives the same effects; however, too large SD for a particular NQ could distort the NMI curves. Using the PZ on the joint histogram generated using the PV and LI methods does not eliminate the ripples. The relative variance, i.e., the ratio of the component variance over the summation of all component variances, of the first two components after correction are higher than those before correction. They contribute more than 94% of the total variance. As shown in Fig. 3, the relative variances of the 3rd to 8th components after correction using some selected combinations of the NQ and the SD of the PZ are generally lower than those before correction. The relative variances after the 9th component before and after correction are about the same. Fig. 4 demonstrates the FA images (row 1) and the color maps (row 2) using the NQ equal to 32 before (column 1) and after (column 2). The images before correction are very noisy and blurred. After correction, the images are clear and the edges are sharpened. The location of the tumor and the lateral ventricle are distinguishable by the surrounding high FA area.

Conclusions: The shifting-theorem method is appropriate for estimation of the mutual information between a pair of images because it does not create additional artifacts. Computational time using shifting-theorem reduces significantly by the approximation using upsampling. Reducing the number of quantization levels or using the Parzen window smoothes and emphasizes peaks on the mutual information cost function. However, insufficient numbers of quantization levels might suppress some important image features and using the Parzen window with too large standard deviation may create artifacts on the NMI curves. Finally, the images after eddy-current distortion correction using the proposed method have been shown to have a good quality based on the reduction of the principal component variances. They also generated the FA images and the color maps of the brain white matter fiber orientation with high visual qualities.

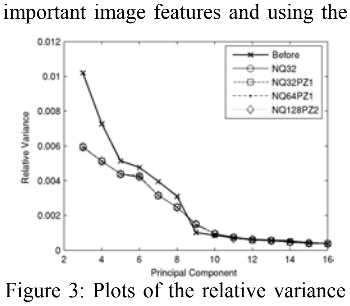

Figure 3: Plots of the relative variance of the principal components from the 3rd to 16th before and after correction using different NQ and PZ.

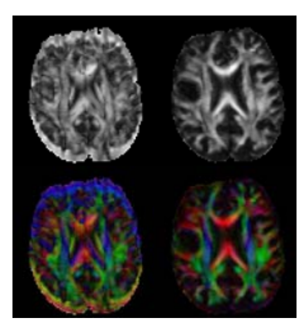

Figure 4: FA images (row 1) and the color maps (row 2). The images before (column 1) and after (column 2) the distortion correction using the NQ=32.

References:

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