Making the Robust Tensor Estimation Approach: "RESTORE" more Robust

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Introduction: The Robust Estimation of Tensors by Outlier Rejection (RESTORE) [1] has been demonstrated to be an effective method for improving tensor estimation on a voxel by voxel basis in the presence of artifactual data points in the diffusion weighted images (DWIs). However, the RESTORE method that combines robust regression and outlier rejection techniques relies on data redundancy [2]. The estimated parameters may not be reliable if the data set does not have enough good data points to correctly identify outliers, or when too many data points have been excluded from the fitting. Moreover, the criteria used for outlier identification in DWIs may not be reliable when applying the same rule to non-DWIs due to intrinsic higher physiologic noise in T2 weighted images. Instabilities on tensor derived quantities have been observed in noisy clinical brain data which causes difficulties in statistic DTI analysis. In this paper, two practical constraints are introduced to further improve the robustness of the RESTORE algorithm.

Methods & Materials: The original RESTORE algorithm used a threshold criterion for outlier identification. The criterion is based on the estimation of signal standard deviation assuming signal variability is affected by the thermal noise in magnetic resonance images (MRIs). The signal standard deviation caused by the white noise is a constant; however, signal variability in non-DWIs are generally much greater than in DWIs in several regions of human brain. The higher signal variability in T2 weighted images may be caused by the high frequency spin inflow effects or due to physiological fluctuations. This fact can be easily observed by comparing the signal intensity in a series of DWIs and non-DWIs, or by comparing the statistics of residuals obtained from the nonlinear least squares fitting. Therefore, the same outlier identification criterion for DWIs may not be suitable for non-DWIs, and a wider tolerance of signal variability should be used for non-DWIs, i.e., the signal standard deviation for non-DWIs will be adjusted based on the following formula: $SD_{non-DWIs} = noise\_kappa \times signal\_ratio \times SD_{DWIs}$, where the signal ratio is defined as the mean signal intensity of all non-DWIs divided by the median signal intensity of non-DWIs, and the noise_kappa is a constant which can be set to 1 or 2. The adjustment is computed only if the signal_ratio is greater than one. A second constraint is then added which uses the condition number [3] to avoid too many data points being excluded as outliers that can yield an ill conditioning in the design matrix. When such situation occurs, some points from the outliers group will be moved back to the good data points group for the final tensor fitting to avoid the ill conditioning.

Twenty healthy volunteers were scanned on a 3.0T GE Excite scanner using an eight channel coil (GE Medical Systems, Milwaukee, WI). Whole brain single-shot echo-planar (EPI) DWI datasets were acquired with the following parameters: TE/TR = 73.4/13000ms, 0.9375x0.9375 mm^2 in-plane resolution, with 54 slices at 2.4mm thickness, b-value of 1000s/mm^2 in 33 noncollinear directions, plus 3 images at a b-value of 0s/mm^2, with two replicates, SENSE acceleration factor = 2. No cardiac gating was performed. Images were corrected for motion and eddy current distortions [4] and EPI distortion [5]. Tensor fitting was performed three times on each subject, once using the original RESTORE algorithm, once using the RESTORE method with adjusted signal variance for b=0 images, and once applying the condition number constraint additionally to outlier identification. Tensor derived quantities were then calculated, including FA and trace(D).

Experimental Results: Figure 1 shows the FA map obtained from the three runs of tensor fitting as described previously. The corrupted bright points in (a) are caused by all of the non-DWIs data points or too many DWIs data points being excluded from the fitting. By adding the proposed two constraints to the outlier rejection process, those bright points have been successfully eliminated.

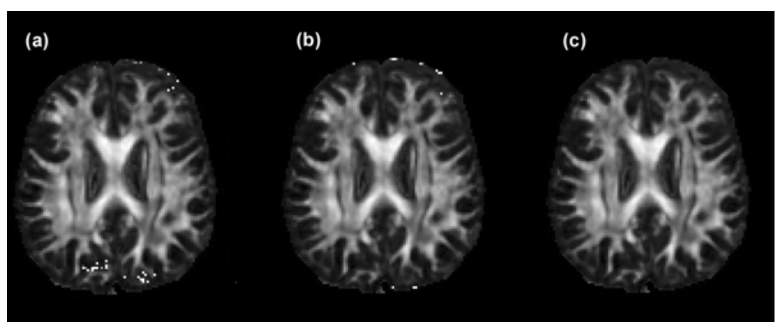

Fig. 1 The estimated FA of selected slice of human brain using (a) the original RESTORE (b) the original RESTORE with adjusted signal standard deviation for non-DWIs (c) the original RESTORE with adjusted signal standard deviation for non-DWIs and condition number for DWIs.

Conclusions: Instabilities in tensor estimation using RESTORE have been observed in clinical human brain data. Those instabilities can come from the intrinsic high frequency spin inflow effects in non-DWIs or from too many data points being excluded from the fitting. This paper proposed two practical constraints in the RESTORE method that reduced the instabilities on tensor estimation. The improvement of the robustness in RESTORE makes it more useful for clinical DTI data analysis.

References: [1] Chang L, et al, *Magn Reson Med* 2005, 53:1088-1095. [2] Bevington P, McGraw-Hill Book Company, New York, NY, 1969. [3] Skare S, et al, *J of Magn Reson* 2000, 147: 340 -352. [4] Rohde GK, et al. *Magn Reson Med* 2004; 51: 103-114. [5] Wu M. et al. *ISMRM* 15th Ann. Meeting, Berlin, 2007, p. 1591.