How Physiological Noise and Artifacts May Impact Clinical Diffusion Tensor Imaging Studies

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Introduction:

Diffusion tensor imaging (DTI) allows non–invasive investigation of structural and architectural features of living tissues and is frequently used for clinical brain studies. There are a number of known image artifacts that can corrupt diffusion weighted images (DWI), which in turn affects DTI derived quantities, including bulk subject motion, EPI distortions and pulsatile motion due to the cardiac cycle. Robust tensor fitting applied on a voxel-wise basis has been proposed for mitigating the effects of artifactual data points that manifest themselves as outlier data (Mangin 2002, Chang 2005). RESTORE robust fitting has shown good performance in Monte Carlo simulations but few quantitative studies of in vivo brain data exist. In this work we characterize the regional distribution of DWI data that are identified as outliers by RESTORE fitting in a typical clinical DTI acquisition and investigate the consequences of outlier rejection on the statistical outcome of DTI population analysis.

Methods:

20 healthy subjects (52.7 ± 9.49 years, 8 male) were scanned on a 3.0T GE Excite scanner (GE Medical Systems). Whole-brain single-shot EPI DWI datasets were acquired with: TE/TR = 73.4/13000ms, 0.9375x0.9375mm2 in-plane resolution, 54 slices, 2.4mm thick, b-value 1000s/mm2, 33 non-collinear directions, 3 images at 0s/mm2, two replicates, SENSE acceleration factor 2, with no cardiac gating. Images were corrected for motion, eddy current (Rohde 2004), and EPI distortions (Wu 2008). Tensor fitting was performed using both a non-linear least squares algorithm (referred to as non-robust fitting), and a newly modified version of the RESTORE robust method (Chang 2009) to identify and reject outliers. During the tensor fitting, along with FA and Trace(D) (TR), maps of the outlier data points are created in order to investigate the regional distribution of outliers in each subject. Following tensor estimation, spatial normalization was performed in order to do a voxel-wise analysis of the population, using a fully deformable tensor registration method (Yang 2008) that includes tissue classification as well as orientation information from the tensors, and performs reorientation of the tensors post normalization. Two analyses of the data were performed. First, an outlier rejection probability map (ORP) was created by taking the mean of the 20 subjects' registered outlier maps. Second, mean and standard deviation (SD) maps of the normalized FA and TR were calculated across the population for both the RESTORE and the non-robust data. Subtraction maps (non-robust minus RESTORE) were calculated to evaluate the differences in variance and in mean between the two fitting algorithms.

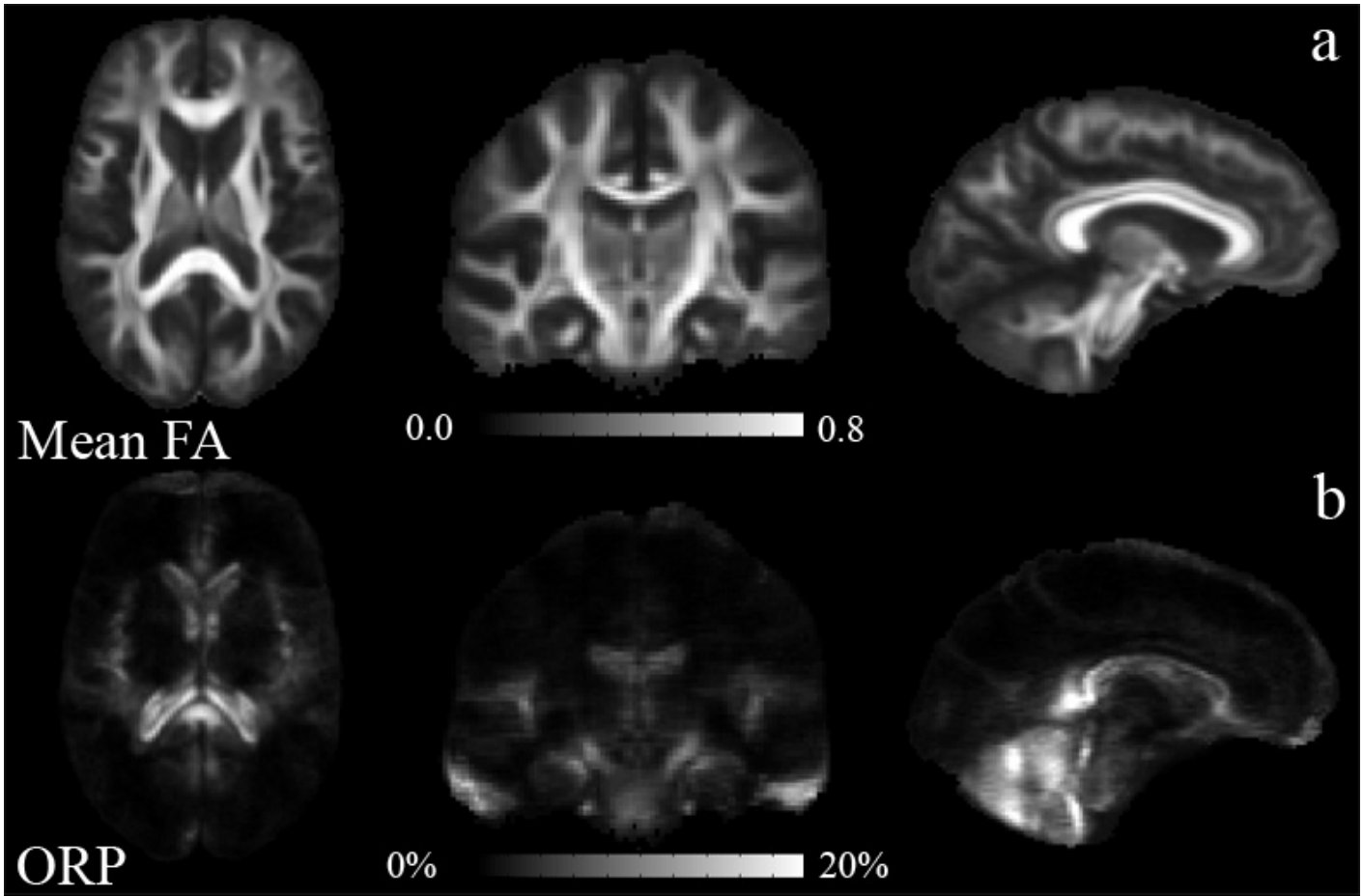
Results:

The brightest values of the ORP map (figure 1) correspond to a 20% rejection of DWI data points as outliers. The ORP map shows a distinct regional distribution of outliers in the population, with a higher percentage in areas including the medial portions of the cerebellum, middle cerebellar peduncles, discrete regions in the temporal lobes which may encompass the fimbria of the hippocampus, the hippocampus and the amygdala, the midline portion of the genu and splenium of the corpus callosum, and insular regions. Subtraction of SD maps for FA and TR shows a decrease in variance with RESTORE robust fitting in the cerebellar regions, and an increase in variance with robust fitting in the ventricular regions. Subtraction of mean FA and TR shows higher

values of FA and TR in cerebellar regions in the population using the non-robust method, while lower values are found in the ventricular and CSF regions. Also of note are a dark area in the genu of the corpus callosum, and a bright area on the splenium of the corpus callosum in FA and the opposite pattern on TR, and bright areas bilaterally in the region of the hippocampus for both FA and TR. Differences of mean and variance of the population between fitting methods shows differences in areas which are regionally consistent with the ORP map. Differences in mean in the cerebellar regions and in the genu of the corpus callosum are consistent with signal dropouts due to the cardiac cycle as previously described (Pierpaoli 2003). In the splenium of the corpus callosum we identify an area affected by artifacts that was not described previously. Curiously, in this area the anisotropy bias is the opposite of what is observed in the genu, i.e. anisotropy is decreased if outliers are rejected.

Conclusions:

Regions of high percentage outlier rejection form well defined clusters on the ORP. This has important implications for the statistical analysis of DTI data; mainly that the statistical power of DTI studies varies in different brain regions. RESTORE generally reduces variance and normalizes the mean value of tensor metrics which may be improperly estimated by the presence of artifacts. The main effect of artifactual data is to produce a bias in the metrics. Thus the effect of artifacts may not be the same for patients and controls. If the two populations have different physiological noise levels, i.e. a different cardiac frequency, statistically significant differences in regions with high probability of outlier rejection must be interpreted with caution as they may not be related to anatomical differences due to disease or pathology. The use of RESTORE can lead to a more accurate evaluation of a population and help reduce spurious findings that may occur due to artifacts in DTI data.



a) Mean FA map of 20 subjects, b) Outlier rejection probability map (ORP) is the average outlier map of the 20 subjects. Note the well defined clusters of outlier data points within the brain.

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Categories

- Diffusion MRI (Imaging Techniques and Contrast Mechanism)