QUALITY ASSESSMENT THROUGH ANALYSIS OF RESIDUALS OF DIFFUSION IMAGE FITTING

A. Leemans[1], C. J. Evans[1,2], and D. K. Jones[1]

[1]CUBRIC, School of Psychology, Cardiff University, Cardiff, Wales, United Kingdom, [2]GE Healthcare, Chalfont St. Giles, United Kingdom

Introduction and Purpose

Diffusion tensor imaging (DTI) has become an important method for investigating white matter (WM) [1, 2]. Quantitative parameters derived from the tensor model, including fractional anisotropy (FA) and mean diffusivity (MD), are widely used to characterize WM in both normal and diseased subjects [3]. To obtain reliable quantitative results, it is important to assess the quality of the DTI data with respect to subject motion, distortions, signal dropouts, etc. prior to further analyses. It is imperative that the acquired images are of similar quality when comparing results between different papers or performing multi-center DTI studies. In this context, we developed a comprehensive DTI quality assessment (QA) tool that provides a 'direct feel' and 'global overview' of the data in an automatic way, based on the analysis of the diffusion tensor model residuals [4]. We show how this exploratory tool can be used to efficiently identify subject motion, signal dropouts, and image distortions, without the need to inspect all the individual DW images.

Methods

Data acquisition and post-processing: Cardiac-gated DTI data (2.4 mm isotropic resolution) were collected from 5 healthy volunteers on a 3 Tesla MR system using a gradient sampling scheme consisting of 6 non-diffusion-weighted (DW) images S_0 and 60 DW images (b = 1200 s/mm^2) in which the gradients were uniformly distributed over the sphere [5]. The tensor model was estimated using a weighted (anisotropic covariance matrix) linear regression approach [6]. The data were masked to exclude non-brain constituents.

DTI QA tool: In the following steps, the DTI QA procedure is summarized:

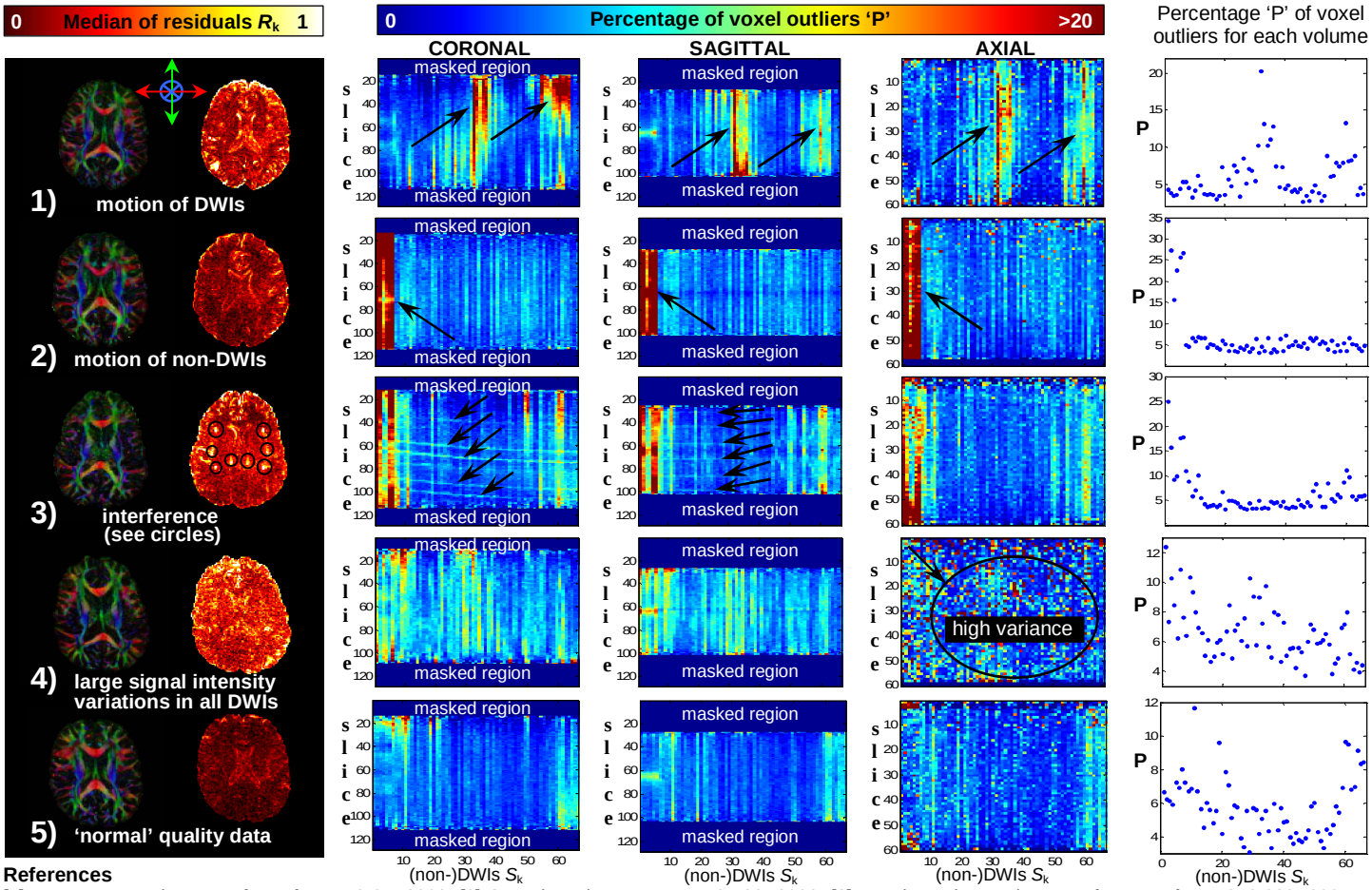
1) After estimating the diffusion tensor **D**, the residual R_k (k = 1,…,66) with respect to each diffusion signal S_k is calculated for each voxel [4, 6], i.e. $R_k = \left| S_k - \exp\left(-\mathbf{D}\cdot\mathbf{b}_k\right) \right|$ with $\mathbf{D} = \left[D_{xx} \;\; D_{xy} \;\; D_{xz} \;\; D_{yy} \;\; D_{yz} \;\; D_{zz} \;\; -\log(S_0) \right]$ and $\mathbf{b}_k = \left[b^k_{xx} \;\; 2b^k_{xy} \;\; 2b^k_{xz} \;\; b^k_{yy} \;\; 2b^k_{yz} \;\; b^k_{zz} \;\; 1 \right]^t$.
2) Determine for each voxel the residual outliers R_i (using non-parametric statistics due to the potential non-Gaussianity of the data distribution), i.e. $R_i \in \left\{ R_k \mid R_k > \left| median\left(R_k\right) - 1.5 \times R_{iq} \right| \right\}$ with R_{iq} representing the inter-quartile range of R_k [7].
3) Calculate the percentage of voxels that are outliers for each axial, sagittal, and coronal slice for each measurement.

Results

In the figure below, each row of images represents a DTI QA of a single subject (1→5). The first column is the directionally-encoded FA map; the second column represents the normalized median R_k of the same slice; columns three, four, and five show the percentage of outliers 'P' for each coronal, sagittal, and axial slice (vertical axis), respectively, for each measurement S_k (horizontal axis); the last column plots 'P' (vertical axis) for each S_k (horizontal axis). Although undetectable from the FA image, the QA tool clearly shows the different acquisitions artifacts, as indicated by the arrows.

Conclusion

Our DTI QA tool, a MATLAB tool that will be released to the DT-MRI community at the ISMRM, allows one to *efficiently* localize data artifacts (subject motion, image distortions, signal dropouts, etc.) that are difficult to detect on the individual (non-)DW images. This tool can also be used to assess the quality of artifact correction schemes.



References

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