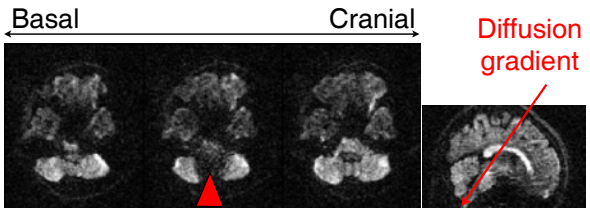
A Gaussian Process based method for detecting and correcting dropout in diffusion imaging.

Jesper Andersson[1] and Stamatios N Sotiropoulos[1]
[1]*FMRIB-Centre, Oxford, Oxfordshire, United Kingdom*

PURPOSE

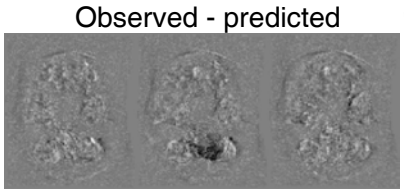
Signal dropout caused by coherent movement (subject or pulsatile movement) during the diffusion encoding is a problem for diffusion imaging. Any component of the movement that is co-linear with the diffusion gradient will lead to dropout, the magnitude of which will depend on factors such as phase-encode band width and if/how partial k-space acquisition is performed. These dropouts will typically affect a whole slice (in the case of subject movement) or a substantial part of the brain (for pulsatile effects) [1]. The consequence for modeling/tractography is that the dropout will be interpreted as high diffusivity along the direction of the diffusion gradient for the slice with dropout. Specifically for pulsatile effects this can cause a systematic overestimation of the diffusivity along the direction of high tissue velocity in basal-medial regions and bias fibre orientation estimation. Our proposed method will detect outliers in a slice-by-slice basis and, instead of "just" rejecting it propose a data-driven replacement for the slice.



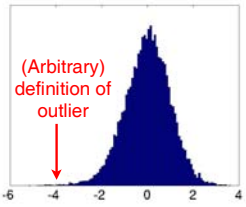
Example of slice with dropout caused by cardiac pulsation

METHODS

We have recently developed a method (EDDY) for simultaneously correcting for eddy current-induced distortions and subject movements [2]. It is based on comparing a Gaussian Process based prediction of the data with the observed data in the native scanner space. The sum-of-squares of the observed difference drives the estimation of the distortion and movement parameters. If observation-minus-prediction has a negative non-zero sum (across voxels) it is indicative of dropout being present in the observed data. Each slice of each diffusion weighted volume yields one such number which allows us to convert them to z-scores and build an empirical distribution of slice differences. The z-scores can be thresholded at an arbitrary level (4 in our examples) to define an outlier. The outlier slice can then be replaced by its prediction for the remaining iterations of EDDY and also for the generation of the final pre-processed data.



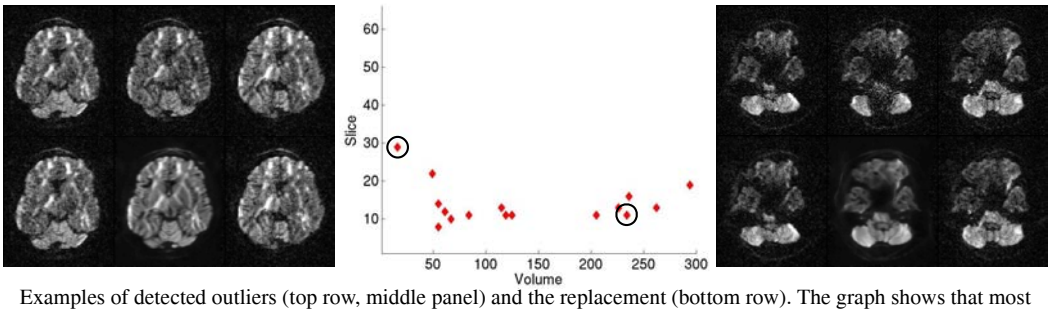
Examples of slice-wise differences between observations and predictions.



Distribution of z-scores for all slice-wise differences.

RESULTS

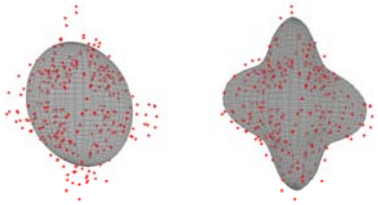
The method has proven to be very sensitive at detecting outliers. When "simulating dropout" by multiplying a slice by some number < 1 it has been able to reliably detect "whole slice" dropout of as little as 2%. The figure to the right shows examples of outliers that were detected and replaced in a dataset with 66 slices and 300 volumes from the HCP project [3,4].



Examples of detected outliers (top row, middle panel) and the replacement (bottom row). The graph shows that most outliers are detected in basal slices where the cardiac pulsation is greatest. The example on the left (from slice 29) is the exception and is probably due to subject movement. Note how in that case the intensity of the whole slice is affected, making it hard to see unless one compares it to the neighboring slices.

DISCUSSION

Unlike previous methods, such as RESTORE [5], our method considers a summary statistic from an entire slice when deciding if a point is an outlier or not. This means that we can achieve higher sensitivity than is possible when considering voxels in isolation. It also makes sense as the nature of the artifact means that it will affect whole slices or at least substantial parts of the brain in a given slice. This is possible because the comparison is performed in the space of the original acquisition, i.e. the observed slice has not been interpolated or processed in any other way. If instead the movement/distortion correction is performed prior to, and independent of, the outlier detection affected and unaffected voxels will be mixed through the interpolation leading to a loss of sensitivity. In addition a severe slice dropout can bias the estimation of movement/distortion. We therefore believe that it is important that the two corrections are incorporated into a framework that performs them simultaneously.


Data (red points) from a crossing fibre voxel and predictions (grey surface) for tensor (left) and Gaussian Process (right)

Another novel aspect of our work is that it detects "outliers" using a non-parametric Gaussian Process framework rather than a specific model (e.g. the diffusion tensor). That means that it is data-driven and not coupled to a specific model and can therefore represent the signal from voxels with complex fibre patterns whereas the diffusion model might instead "detect" outlier points as demonstrated in the figure above. As the outlier detection is not tied to fibre orientation estimation the method can provide corrected data useable by all HARDI approaches, for example parametric [6] and non-parametric [7], and single and multi-shell [8].

REFERENCES

1. Jones & Pierpaoli, 2004, ISMRM:225. **2.** Andersson et al., 2012, ISMRM:2426. **3.** Van Essen et al., 2013, NeuroImage:80:62-79. **4.** Sotiropoulos et al., 2013, NeuroImage 80:125-143. **5.** Chang et al., 2005, MRM:53:1088-1095. **6.** Behrens et al., 2007, NeuroImage 34:144-155. **7.** Descoteaux et al., 2007, MRM, 58:497-510. **8.** Wu & Alexander, 2007, NeuroImage 36:617-629.