## **RESDORE:** Robust Estimation in Spherical Deconvolution by Outlier Rejection

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<u>Purpose</u> Corrupted diffusion-weighted (DW) signals can have pronounced negative effects on derived indices [1]. One solution, RESTORE, [1,2] is to exclude corrupted signals from the tensor model fitting processes. Taking inspiration from this approach, we have developed a novel pipeline that extends the principle to robust recovery of the fibre orientation distribution functions (fODF) in spherical deconvolution methods. RESDORE (<u>Robust Estimation in Spherical Deconvolution by Outlier RE</u>jection) detects outliers as non-axially symmetric signal components, and rejects them improving the fit and recovery of fODF.

Method Voxels that are likely to contain outliers are first identified through standard A goodness of fit criteria (errors above 3 standard deviations between signal predicted by fODF fit and actual measurements [1][2]). The core algorithm resembles an amalgamation of Richardson-Lucy (R-L) deconvolution [3] and a non-negative sparse coder (NNSC) training phase [4]. We modify R-L by adding an isotropic element to the signal dictionary (the 'H' matrix in [3]) and a dictionary update step within the iterative deconvolution (Eq. 1, [4]). Compared to standard NNSC, the dictionary is not randomly initialised - we instead use the modified R-L dictionary consisting (mainly) of axially symmetric fibre response functions – C and the update step is modified to correct fitting errors by manipulating the isotropic element only. The result is that where the observed signal is adequately described by a model of signal = fODF \* axially symmetric fibre response functions, errors with respect to signal and the current fODF estimate can be corrected by improved weights on the axially-symmetric  $\mathbf{D}$ dictionary elements. However, where the model does not hold, common non-axially symmetric outliers necessitate increased weighting of the isotropic signal component during the dictionary update/correction step since this is the only mechanism through which they may be explained. In a sense, the isotropic element acts as a 'sink' for non-symmetric errors, resulting in improved fODF fits with the axially-symmetric model. Outliers are detected by examining the altered isotropic dictionary element, and identifying components with a median absolute deviation outside 3 standard deviations.



Eq. 1  $H = H - \mu ((HF - S) * F^{T})$   $H = dictionary, F = weights (fODF), S = observed signal, <math>\mu = update weighting (\sim 0.05)$ 

**Results** Figures A-D provide an example of algorithm performance. A shows the fODF derived from R-L for an uncorrupted input (single fibre, FA=0.7, b=2000s/mm<sup>2</sup>, SNR=50), **B** shows the fODF after simulating signal corruption (directions 18 and 42 of the 60 direction set have been attenuated to 30% of expected value). **C** demonstrates the directed component of the fODF after RESDORE. **D** displays distortions of the isotropic component that were learned to compensate for the drop out (x axis representing directions 1-60). To demonstrate sensitivity and specificity with slice-wide corruption we have 'corrupted' 5 mid-brain axial slices (b=1200s/mm<sup>2</sup>, 60 directions, 5921-6234 voxels/slice) by further attenuation of each signal direction in turn by between 0 and 100% of the measured value. Figure **F** shows (1) the rate of successful detections without false positives (blue, scaled 0-1), (2) successful detection as part of a larger set (possible false positives, red) and (3) the number of false positives (cyan, scaled to right axis). Figures **G** and **H** extend this experiment to smaller scales (9 voxels/single voxel respectively) through simulation. Here we generate crossing fibres (b=2000s/mm2, 60dir, random crossing angles/orientation, 100 repetitions) and corrupt each gradient in turn through additional signal attenuation. Measurements/colour coding remains the same.

**Discussion/Conclusion** We have outlined a novel method for outlier rejection in spherical deconvolution methods capable of preserving signals in complex fibre architectures. By controlling the number of voxels that are simultaneously processed (e.g. by selecting specific regions or using a sliding kernel) we are able to trade sensitivity with local specificity as required. When processing a large number of voxels (e.g. whole slices) the averaging effect of the dictionary update step allows us to robustly detect small global corruptions (15%+ additional attenuation) with a low probability of false positive results while correctly excluding very localized corruption that may affect individual voxels/small regions. In the case of more localised corruption, simulations **G** and **H** show that our algorithm remains effective at detecting common artefacts across small samples (**G**, 9 voxels, robust detection of corruptions > 15%, negligible false positives when corruption > 50/60%) or in individual voxels (**H**, 1 voxel, robust detection of corruptions > 30%, minimal false positives). In practice it is therefore best to employ this algorithm in a hierarchical manner, beginning with slice wide application (where goodness of fit indicates it is appropriate) then proceeding to investigate local issues, scaling the testing kernel according to the proximity/density of indicated outliers (e.g. you may expect to observe coherent errors clustered in areas known for cardiac pulsation, therefore choose to apply a multi-voxel kernel in such areas).



[1] Chang. Et. Al. 2005. Mag. Res. Med. 53(5):1088-1095 [2] K. Pannek *et al.* 2012. NeuroImage 63:835-842 [3] Dell'Acqua et. Al. 2007. IEEE TBE 54(3):462-472 [4] P.O. Hoyer, Non-negative sparse coding, 2002, Proc. IEEE Neural Networks for Sig. Proc. 12